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International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Intelligent monitoring of physical exercise behavior and personalized compliance improvement strategy for community public health

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SUMMARY: *The difficulty of physical exercise promotion in community public health is not to give general recommendations, but to continuously identify residents' exercise status and improve long-term compliance. In this paper, an intelligent monitoring and personalized intervention framework for community scenes is constructed, which integrates wearable sensor signals, mobile logs and follow-up information, and conducts multi-source modeling of residents 'exercise behavior. After data preprocessing and feature representation, the residents' motion portraits are further generated, and the activity types, load changes and execution trends are distinguished by combining the time series recognition and state evaluation model. The motion types, intensity, duration and reminder timing are adjusted through the dynamic feedback mechanism. The experimental results show that the proposed method achieves 93.8% Accuracy and 92.4% Macro-F1 on the behavior monitoring task, and the plan completion rate is improved to 84.9%. The duration of moderate to high intensity physical activity per week of residents is significantly increased. The results show that integrating behavior monitoring, state judgment and compliance optimization into the unified computing closed loop can more effectively support daily exercise management in community public health.*

KEYWORDS: *Community public health; Exercise behavior monitoring; Compliance improvement; Personalized intervention*

1 Introduction

With the concept of community public health governance gradually shifting from "disease treatment" to "risk prevention" and "active health promotion", physical exercise plays an increasingly prominent role in the prevention and control of chronic diseases, the maintenance of physical function and healthy aging. Especially in community Settings, regular physical activity is not only related to the improvement of individual physical fitness, but also directly affects the long-term effectiveness of primary public health services. In recent years, the continuous popularity of smart bracelets, sports watches, mobile phone sensors and community health management platforms has enabled low-cost and continuous recording of steps, heart rate, activity duration, exercise frequency, energy expenditure and sedentary time. This technical condition provides a realistic basis for the fine identification and long-term tracking of residents 'exercise behavior, and also promotes community sports intervention to gradually enter the data-driven stage.

Although the acquisition ability of exercise data has been significantly improved, the existing community exercise management methods still generally rely on unified indicators,

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https://doi.org/10.65102/is2026570
Published: 30 April, 2026

fixed thresholds or empirical recommendations. Many intervention programs emphasize "how much exercise should be done", but rarely answer questions with more practical value, such as "in what state are certain residents more likely to stop exercise", "what kind of reminder is more acceptable", and "how should people with different health backgrounds adjust exercise intensity and rhythm". Due to significant differences in age structure, underlying diseases, sleep patterns, digital literacy and past sports experience, static recommendations are often difficult to adapt to the real community population, resulting in implementation bias, decreased compliance and insufficient platform usage viscosity. It can be seen that the exercise promotion in community public health is not only a problem of "recommended content generation", but also a continuous optimization problem involving behavior recognition, state evaluation and dynamic feedback.

The core challenge of this paper is how to build an intelligent monitoring system that can continuously perceive residents 'physical exercise behavior, accurately assess behavior status, and simultaneously improve exercise compliance in community public health scenarios. Existing research has made some progress in wearable monitoring, activity classification and digital health intervention. However, the monitoring model and intervention strategy are often designed separately. Although the system can identify whether residents are moving or not, it may not be able to determine why they are not moving or how to promote behavior maintenance more effectively. Without the joint modeling of individual state changes, historical execution trajectories and feedback response characteristics, exercise promotion is easy to stay at the one-time prompt level, and it is difficult to form stable health behavior improvement effects.

In response to the above problems, this paper proposes a framework for intelligent monitoring and personalized compliance improvement of exercise behavior for community public health from the perspective of computer modeling. By integrating the physiological and motor data collected by wearable devices, mobile exercise logs and community follow-up information, a multi-source exercise behavior database of residents was constructed. On this basis, the residents' motion portrait modeling is completed through feature extraction and representation learning, and the machine learning method is used to recognize and evaluate the states of walking, jogging, aerobics, resting and sedentary. Furthermore, according to residents' historical execution records, recent state fluctuations and feedback acceptance, the system dynamically adjusts the motion reminder time, recommendation frequency, load level and incentive mode, so as to form a closed-loop optimization mechanism of "monitoring-identify-appraisal-intervention-feedback".

The research value of this paper is mainly reflected in two aspects. On the one hand, the research advances the community physical exercise management from traditional experience judgment to a computable, quantifiable and traceable intelligent analysis framework, which provides more real-time and adaptive technical support for community public health governance. On the other hand, this paper does not stop at the behavior record level, but further couples the recognition results with the compliance improvement strategy, so that the system can implement differentiated interventions according to the real status of residents, which is of practical significance for improving the long-term exercise adherence rate of community residents and optimizing the allocation of public health services.

The rest of this paper is organized as follows: Section 2 reviews the related research on exercise behavior monitoring, personalized digital intervention and compliance optimization; The third part introduces the construction method, sample situation and preprocessing process of community sports behavior monitoring data. The fourth part elaborates the residents 'exercise portrait construction, behavior recognition and status evaluation model, as well as the personalized compliance improvement and dynamic feedback mechanism. The fifth part gives the experimental setup, monitoring effect analysis, compliance improvement results and community application evaluation. Section 6 summarizes the paper and concludes the study.

2 Related Research

As community health management gradually shifts from periodic publicity to continuous data governance, physical exercise research has also begun to shift from the static judgment of "whether to participate in exercise" to the computational problem of "how to continuously identify, explain and improve exercise behavior". With the popularity of wearable devices, mobile phone sensors and mobile health platforms, steps, heart rate, activity intensity, sedentary time, trajectory information and interaction logs can be continuously collected, which provides a data basis for intelligent monitoring of community crowd movement behavior [1, 2]. But data alone does not automatically equal effective intervention. How to extract residents 'movement status from multi-source heterogeneous data, how to convert monitoring results into personalized feedback, and how to improve compliance in the long-term use process are still the focus of current research. Focusing on the theme of this paper, the existing work can be generally summarized into several paths, such as exercise behavior perception and recognition, personalized digital intervention, persuasion strategy and timing optimization, and compliance influence mechanism analysis. A comparison of representative studies is shown in Table 1.

Longhini et al. [1] summarized the application effects of wearable devices in promoting physical activity and reducing sedentary behavior from the review level, and pointed out that continuous monitoring can improve the intervention accuracy, but there are still differences between different devices in signal stability, index consistency and population adaptability. Farrahi and Rostami[2] further introduced machine learning into the study of physical activity, sedentary and sleep behaviors, and showed that classification models and temporal feature extraction techniques can significantly improve the quality of activity recognition. However, this kind of research focuses more on the "accuracy of recognition", and less on how to improve the behavior in the community scene after recognition. In other words, monitoring has improved, but the chain of computation from monitoring to compliance optimization has not yet been fully opened.

In terms of digital health intervention and personalized strategy design, Ten Klooster et al. [3] systematically composes eHealth personalization methods and believes that user profiling, rule adaptation and data-driven recommendation are the current mainstream technical routes, but many platforms are still in the shallow stage of personalization, that is, static grouping according to age, gender or past preferences. Lack of continuous response to fluctuations in real-time behavior. Brons et al. [4] specifically examined machine learning personalized persuasion strategies for promoting physical activity in mHealth, and pointed out that reinforcement learning, contextual multi-armed slot machines, and supervised learning can all be used for intervention content selection and reach mode optimization. This direction has shown strong computational potential, but in real community public health scenarios, models often face problems such as uneven sample distribution, insufficient digital use ability of elderly groups, and sparse feedback labels, which limit the ability of policy transfer.

Compliance itself is increasingly being studied as an independent object. Xu et al. [5] discussed the influencing factors of compliance in intelligent personalized exercise prescription through qualitative research, and found that execution burden, feedback understandability, self-efficacy and external support jointly affect long-term adherence. This study reveals that compliance is not a single behavioral result, but a dynamic process driven by multi-dimensional factors coupling. However, it mainly develops from the level of behavioral mechanism, and has not yet formed a complete method for computable modeling and online policy updating. Ho et al. [6] verified the intervention effect of wearable activity trackers and step-by-step goal setting in the elderly population, and the results showed that step-by-step goals and visual feedback were helpful to improve the activity level and related health indicators. This shows that the closed loop of "goal-feedback-readjust" has practical effectiveness, but the goal update in this study is still biased towards preset rules, and machine learning has not yet been fully used to model individual response differences.

The study of digital exercise intervention for special health groups also provides reference experience for community public health. Chua et al. [7] confirmed in adults with type 2 diabetes that intervention based on wearable technology can improve physical activity levels, but the intervention effect fluctuates greatly between different studies, suggesting that the problem of individual heterogeneity is still prominent. Waki et al. [8] proposed a personalized mHealth intervention program based on social cognitive theory, which combined goal setting, behavior feedback and patient status, and emphasized that the intervention content should match the user's current executable ability. This idea is highly related to the improvement of compliance of community residents, which is the focus of this paper. However, its method emphasizes more on the intervention design framework and has limited attention to the exercise behavior recognition model and state assessment model itself. Ang et al. [9] proposed the suggestion of allocating steps by hour to help the working population and the elderly reach the daily goal more stably. This kind of granular recommendation indicates that the intervention timing and task segmentation method will directly affect the execution quality, but the generation of suggestions is still based on empirical statistics and lacks joint learning of long-term behavior trajectory.

Table 1: Comparison of technical paths and limitations of representative related studies

Study	Main Object	Technical Path	Main Contribution	Main Limitation
Longhini et al. [1]	Wearable-based physical activity promotion research	Umbrella review	Summarized the overall effects of devices in promoting physical activity	Lacked specific online modeling methods
Farrahi and Rostami [2]	Physical activity / sedentary behavior / sleep recognition	Machine learning-based behavior classification	Strengthened the computational foundation for multi-behavior recognition	Focused more on recognition than on subsequent intervention
Ten Klooster et al. [3]	eHealth personalization	Review of individual profiling and rule adaptation	Clarified personalized design pathways	Most systems lacked dynamic adaptation
Brons et al. [4]	mHealth persuasive strategies	Machine learning-based personalized intervention	Showed that algorithms can improve intervention matching	Limited generalizability in real community settings
Xu et al. [5]	Exercise prescription adherence	Qualitative analysis	Revealed the mechanism underlying adherence formation	Lacked a computable closed-loop model
Ho et al. [6]	Physical activity in older adults	Wearable tracking + stepwise goals	Verified the effectiveness of progressive goal feedback	Goal updating depended on predefined rules
Chua et al. [7]	Exercise intervention for adults with diabetes	Systematic review and regression analysis	Demonstrated the positive effects of wearable interventions	Population heterogeneity led to fluctuating effects
Waki et al. [8]	Personalized mHealth intervention	State-aware behavioral feedback	Emphasized feasibility and behavioral support	Weak in behavior recognition and state modeling
Ang et al. [9]	Time-segmented step-count recommendation	Statistical modeling and recommendation allocation	Improved the operability of daily goal attainment	Did not form a long-term adaptive optimization mechanism

Based on the existing research, it can be seen that the related work has provided a solid foundation in exercise data collection, activity recognition, personalized intervention and compliance analysis respectively, but there are still three obvious gaps: First, many studies treat "monitoring" and "intervention" separately, the former emphasizes recognition accuracy, the latter emphasizes behavior promotion, and there is no unified state expression and linkage update mechanism between the two. Second, personalization often stays in static stratification or short-term rule adaptation, which is difficult to dynamically adjust according to residents 'continuous motion trajectories, fatigue changes and historical execution results. Thirdly, the population composition in community public health scenarios is more complex, including both middle-aged and elderly chronic disease risk groups and ordinary residents with unstable work and rest. The evidence of existing models on cross-population and cross-context transfer is still insufficient. Based on this, this paper puts the intelligent monitoring of exercise behavior and personalized compliance improvement into the same computing framework, and tries to construct a closed-loop technical solution that can serve community public health governance through multi-source data modeling, residents 'motion portrait, behavior recognition and status evaluation, and dynamic feedback optimization.

3 Construction and preprocessing of community sports behavior monitoring data

3.1 Data source and sample description

The exercise behavior monitoring for community public health is not suitable for directly copying the sampling logic of laboratory data sets. The physical activities of community residents have obvious life embeddedness: some of them occur in the morning or evening walking period, some are distributed in fitness square, community activity room and home training space, and some are fragmented and intermittent light intensity activities. Therefore, the data layer design of this paper does not take a single device record as the core, but constructs a sample system of three parallel sources of "wearable sensor data, mobile terminal behavior log, and community follow-up information", which is used to describe the continuous state and change trajectory of residents 'real exercise behavior. Figure 1 shows the data source and sample composition framework of this paper.

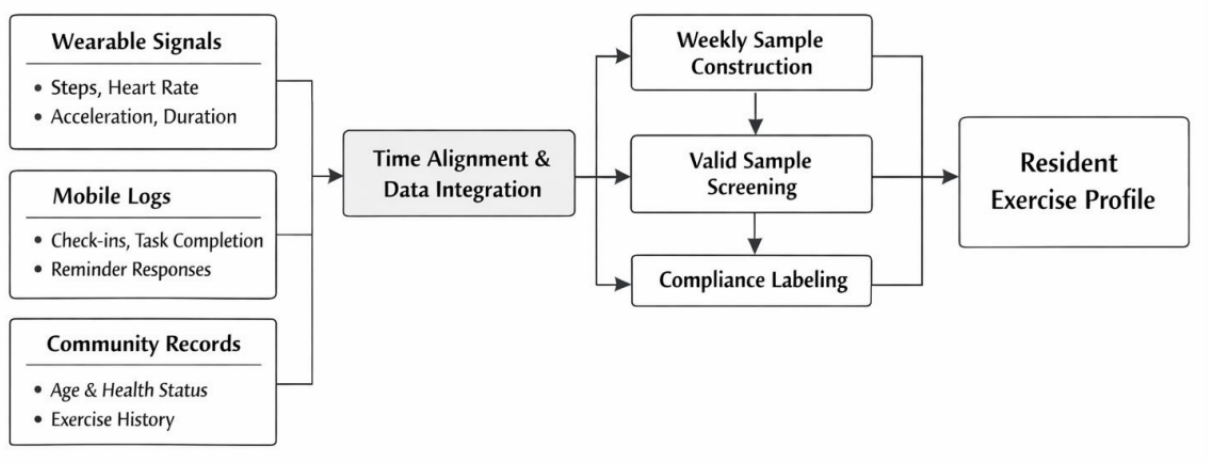

Figure 1: Community movement behavior monitoring data sources and sample composition framework

The original observation of the ith resident at time t, defined as:

$$x_{i,t} = [s_{i,t}, m_{i,t}, c_{i,t}] \tag{1}$$

where $s_{i,t}$ represent the physiological and motion signals collected by wearable devices, including the number of steps, heart rate, acceleration and activity duration. $m_{i,t}$ represents the mobile terminal log information, including the frequency of clocking in, the completion of training tasks and the reminder response behavior. $c_{i,t}$ represents community follow-up and basic attribute information, including age, chronic disease risk, previous exercise habits, and self-rated physical activity level. The three types of data together constitute the multi-source input of community movement monitoring, rather than isolated auxiliary fields.

In order to ensure that the subsequent modeling can take into account the time series stability and individual differences, this paper takes the natural week as the basic statistical unit, and integrates the continuous observations into the resident level sample matrix:

$$X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,T}\} \tag{2}$$

where T is the number of effective sampling periods in the observation period. The purpose of such processing is not only to retain the movement intensity changes of residents in different time Windows, but also to provide continuous state context for subsequent behavior recognition models. Compared with the single measurement, the weekly scale sequence is closer to the actual rhythm of the community health intervention and better reflects the process of adherence formation.

The sample selection follows the principle of "multi-source alignment, behavior interpretation, and time series traceability". If a resident only has scattered steps records and lacks training logs or basic health information, it is difficult to support subsequent state discrimination and policy optimization, so it is not included in the core modeling set. For the remaining samples, this paper further defines the effective exercise exposure intensity:

$$e_i = \frac{1}{T}\sum_{t=1}^{T} d_{i,t} \cdot q_{i,t} \tag{3}$$

Here, $d_{i,t}$ represents the motion duration in the t-th period, and $q_{i,t}$ represents the intensity weight in the corresponding period. This index is used to measure the average effective activity level of residents during the observation period, which not only avoids judging the quality of exercise by the number of steps, but also allows distinguishing between brisk walking, aerobics, equipment training and low-intensity daily movement.

Considering that the research goal of this paper is not only to monitor exercise behavior, but also to identify compliance status, individual compliance markers are further constructed:

$$y_i = \begin{cases} 1, & \dfrac{n_i^{done}}{n_i^{plan}} \geq \theta \\ 0, & \dfrac{n_i^{done}}{n_i^{plan}} < \theta \end{cases} \tag{4}$$

Here, n_i^{plan} is the number of planned exercises in the observation period, n_i^{done} is the actual number of completion, and θ is the threshold for compliance determination. The definition makes the sample have the significance of behavior recognition and management decision at the same time, and provides a unified label basis for the subsequent "monitor-evaluation-feedback" closed-loop modeling.

3.2 Data preprocessing and feature representation

The original data of community movement behavior monitoring has obvious heterogeneity and disturbance. Acceleration, step rate and heart rate sequences uploaded by wearable devices often contain device jitter, short-term interruption and posture deviation. Although mobile logs can supplement clocking, task completion and reminder response information, the time granularity is not always consistent with the sensing signal. If this kind of data is directly input into the recognition model, the model is easy to misjudge the incidental noise as motion changes, and it is difficult to stably depict the real activity rhythm of residents. Based on this, in this paper, the preprocessing is divided into four links: signal smoothing, scale unification, time segmentation and feature representation, whose processes are shown in Figure 2.

Figure 2: Flow chart of data preprocessing and feature representation

For the continuous observation sequence x_t, this paper first smoothen processing to weaken the interference of high-frequency jitter on subsequent recognition:

$$\tilde{x}_t = \alpha x_t + (1-\alpha)\tilde{x}_{t-1}, \quad 0 < \alpha < 1 \tag{5}$$

Here, $\tilde{x}_t$ is the smoothed signal and α is the smoothing coefficient. This processing is more suitable for the non-rigorous experimental data in the community scene, and can retain the continuous change of residents 'exercise intensity without excessive damage to the trend information. After denoising, we perform normalization on features from different sources to remove any bias caused by dimension differences:

$$z_{i,j} = \frac{x_{i,j} - \mu_j}{\sigma_j} \tag{6}$$

where $x_{i,j}$ represent the original value of the ith sample in the JTH dimension, μ_j and σ_j represent the mean and standard deviation of the features in this dimension, respectively. After normalization, variables such as heart rate, step number, duration and response frequency are mapped to a comparable scale space, which is more conducive to model convergence and feature fusion. In order to preserve the temporal structure of the motion behavior, the sliding window method is used to segment the sequence. For the KTH time window, is defined as:

$$W_k = \{z_k, z_{k+1}, \dots, z_{k+w-1}\} \tag{7}$$

Here, w is the window length. A certain overlap is set between the Windows to preserve the transition segments such as fast walking to slow walking, motion to rest. Compared with single point sampling, this method can better reflect the continuity and stage fluctuation of exercise behavior of community residents.

In the feature extraction stage, this paper not only retains simple statistics, but also constructs a more descriptive window representation combined with motion monitoring tasks. Taking the triaxial acceleration as an example, the signal amplitude area within the window is defined as:

$$SMA_k = \frac{1}{w}\sum_{t \in W_k}\left(|a_t^x| + |a_t^y| + |a_t^z|\right) \tag{8}$$

This metric can be used to characterize the overall activity load within a unit window. At the same time, the features of average heart rate, heart rate change slope, step frequency fluctuation, task completion rate and reminder response delay are jointly extracted and spliced into a unified representation vector, which is used as the input of the subsequent residents 'exercise portrait construction and behavior recognition model. The feature representation thus formed not only retains the dynamic information of physical activity itself, but also incorporates the execution signals directly related to compliance in the process of community management, so that the data layer can naturally connect the subsequent state assessment and personalized feedback module.

4 Intelligent monitoring and compliance optimization of exercise behavior

4.1 Construction of residents' movement portraits

In community public health scenarios, the function of residents 'motion portraits is not only to label individuals as "active" or "inactive", but to compress the behavioral rhythm, physiological load, and execution stability scattered in multi-source data into a computable and updated state representation. Without this layer of modeling, even if the system can identify the type of activity such as walking, jogging, or machine training, it is difficult to further determine whether a resident is currently more suitable for maintenance, intensification, or withdrawal exercise program. Based on this, this paper defines residents 'exercise portrait as a structured vector composed of basic attributes, exercise behavior characteristics, physiological response characteristics and compliance performance characteristics, and serves as the input core of subsequent status evaluation and personalized feedback. For the ith resident, let its portrait vector be:

$$p_i = [b_i, a_i, h_i, c_i] \tag{9}$$

Here,b_i represents basic attributes such as age, previous exercise habits and chronic disease risk, a_i represents behavioral characteristics such as frequency, duration, intensity and activity type distribution, h_i represents physiological response characteristics such as heart rate fluctuation, recovery speed and load change, and c_i represents compliance characteristics such as stage clogging rate, plan completion rate and reminder response. This way of representation makes the portrait no longer stay in demographic classification, but can reflect the multi-dimensional state of "what has been done, how it has been done, and whether it is sustained".

In order to identify the differences in movement patterns between residents, this paper introduces cluster analysis in the portrait construction stage to group the standardized feature set. The objective function is written as:

$$J = \sum_{k=1}^{K} \sum_{p_i \in C_k} \| p_i - \mu_k \|^2 \tag{10}$$

Here, C_k is the KTH portrait cluster and μ_k is the corresponding cluster center. The clustering results can divide the residential areas into several portrait categories such as "low frequency low stability", "middle frequency fluctuation" and "high frequency stable", so as to provide a hierarchical basis for intervention strategies. Compared with the experience grouping, this method is able to more realistically reflect the differences in the pace of life, physical ability basis and execution habits of the community residents. Considering that compliance changes often lag behind single exercise performance, this paper further defines a phase compliance trend indicator:

$$r_i = \frac{1}{L} \sum_{t=T-L+1}^{T} \frac{m_{i,t}^{done}}{m_{i,t}^{plan}} \tag{11}$$

Here, $m_{i,t}^{done}$ and $m_{i,t}^{plan}$ represent the number of motor tasks actually completed and scheduled in time period t, respectively, and L is the length of the backtracking window. This index is used to describe the recent execution status of residents, rather than judging only by a certain completion. On this basis, this paper uses weighted fusion to form the final portrait score:

$$s_i = \sum_{j=1}^{d} w_j \, p_{i,j} \tag{12}$$

where $p_{i,j}$ is the JTH dimension feature of the profile vector, and w_j is the corresponding weight. The scoring results do not directly replace the original features, but are used as the profile summary variables, which are input into the subsequent behavior recognition and feedback optimization module together with the clustering categories. The residents' movement portraits thus constructed not only retain the individual differences in the community scene, but also provide a traceable and updatable state basis for the compliance improvement strategy. The overall construction process is shown in Figure 3

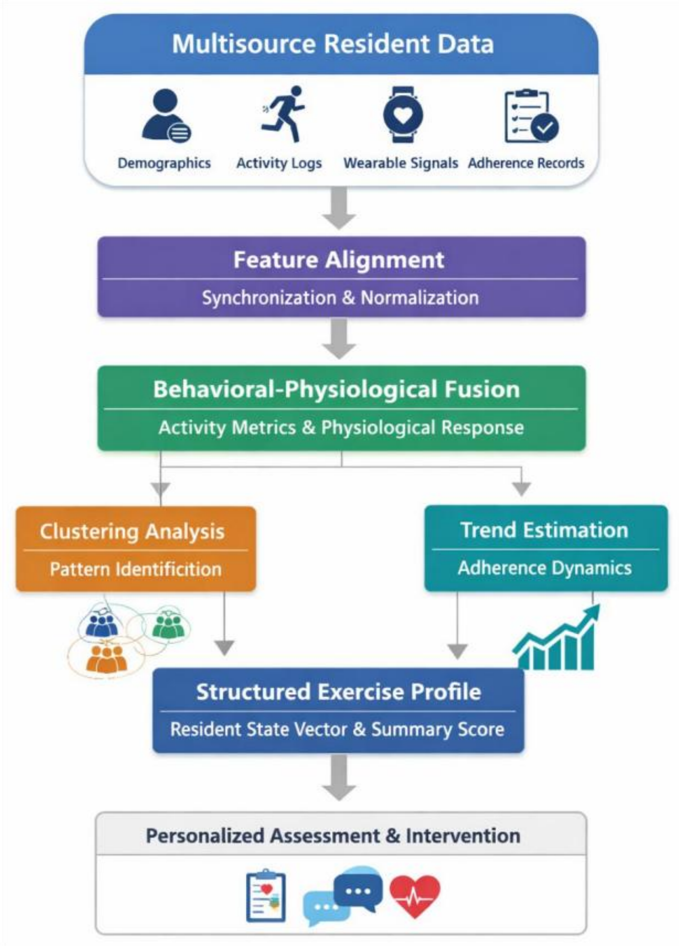

Figure 3: Flow chart of resident movement portrait construction

4.2 Behavior recognition and state evaluation model

In community public health scenarios, movement behavior recognition is not an isolated action classification problem. The activity sequence of residents often includes walking, stopping, jogging, equipment training and non-sports movement, and the performance of the same movement on the sensing signal is not completely consistent under different age groups and different physical abilities. If only relying on single-moment features for discrimination, the model is easy to misidentify short-term disturbances as behavior transitions, and it is also difficult to further determine whether the resident is in a state of stable execution, high load or decreased compliance. Based on this, this paper constructs an integrated model of "temporal behavior recognition-state comprehensive evaluation", which jointly inputs the window-level feature sequence and residents 'motion portrait into a unified framework, and outputs the stage state results while completing the activity type recognition, which provides a basis for subsequent personalized feedback. Its structure is shown in Figure 4.

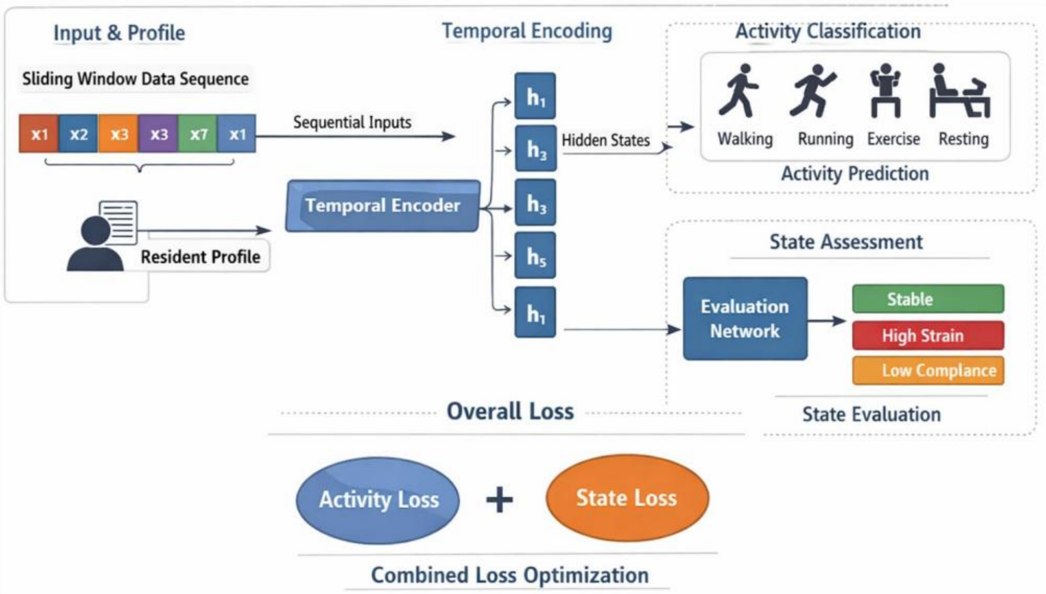

Figure 4: Structure diagram of behavior recognition and state assessment model

Let the input of the ith resident over T consecutive time Windows be represented by $X_i = \{x_{i,1}, x_{i,2}, \dots, x_{i,T}\}$, and the portrait vector is p_i. In this paper, the temporal encoder is first used to extract the dynamic representation and obtain the hidden state:

$$h_{i,t} = \phi(x_{i,t}, h_{i,t-1}) \tag{13}$$

Here, $\phi(\cdot)$ represents the temporal update function, which is used to preserve the motion persistence, rhythm change and short-term transition information. Compared with static classifiers, this processing method is more suitable for behavior sequences with frequent switching and intermittent execution in community scenarios.

In the action recognition layer, the model maps the temporal features to specific activity classes and outputs the probability that the TTH window belongs to the KTH action class:

$$P(y_{i,t} = k) = \frac{\exp(w_k^T h_{i,t} + b_k)}{\sum_{j=1}^{K} \exp(w_j^T h_{i,t} + b_j)} \tag{14}$$

Here, K represents the number of behavioral categories, including categories such as walking, jogging, aerobics, equipment training, and resting. This layer solves the problem of "what residents are doing at the moment", but community health management is more concerned about "whether this behavior is in a reasonable and sustainable state of execution". Therefore, this paper further fuses the temporal representation and portrait information to construct the state evaluation score:

$$u_i = \sigma(v^\top[\bar{h}_i, p_i] + c) \tag{15}$$

where $\bar{h}_i$ is the aggregated representation of hidden states within the observation window, $[\cdot]$ represents vector concatenation, and $\sigma(\cdot)$ is the Sigmoid function. The higher u_i is, the closer residents are to the state of stable participation, load adaptation and good compliance. Otherwise, it suggests the risk of execution fluctuation, fatigue accumulation, or decreased willingness to participate.

In order to balance the accuracy of behavior recognition and the stability of state assessment, this paper uses the joint loss function for training:

$$\mathcal{L} = \lambda_1\mathcal{L}_{act} + \lambda_2\mathcal{L}_{state} \tag{16}$$

Here $\mathcal{L}_{act}$ is used to constrain the action classification result, $\mathcal{L}_{state}$ is used to constrain the state evaluation output, and λ_1, λ_2 are the weight coefficients. The significance of joint learning is that the model no longer treats action discrimination and state judgment separately, but lets them correct each other in the same representation space. The results obtained in this way can not only identify the actual movement behavior of residents, but also more accurately describe whether the residents are in the stage of reminding, adjusting or strengthening incentives, so as to provide a state basis that can be directly invoked for the subsequent compliance optimization module.

4.3 Personalized compliance improvement and dynamic feedback mechanism

The personalized compliance improvement module is not a mechanical push of existing exercise recommendations, but a feedback loop that connects residents' current status, recent execution results and community intervention resources to form a sustainable update. For community public health, the real difficulty often lies not in making general recommendations about "should move" but in getting affordable and consistent action plans to residents of different ages, physical abilities, and life rhythms. Based on this, this paper designs the module as the output layer of the method system, which converts the above behavior recognition and state assessment results into executable intervention suggestions, and automatically modifies them according to the feedback after each round of exercise. Let the intervention program oriented to resident i at time t be denoted by:

$$g_{i,t} = [a_{i,t}, l_{i,t}, d_{i,t}, \tau_{i,t}] \tag{17}$$

Here, $a_{i,t}$ represents the type of recommended activity, $l_{i,t}$ represents the intensity level, $d_{i,t}$ represents the duration, and $\tau_{i,t}$ represents the reminder or reaching time. Unlike the fixed motion prescription, this scheme is not a pre-written template, but a dynamic output driven by the current state. The system selects the optimal intervention action according to the resident state vector $s_{i,t}$:

$$g_{i,t}^* = \arg\max_{g\in\mathcal{G}} \pi(g \mid s_{i,t}) \tag{18}$$

Here, G is the set of candidate interventions and $\pi(\cdot)$ is the policy function. The results thus obtained are able to simultaneously account for recent activity load, compliance trends, and reminder sensitivity, bringing the recommendations closer to the actual executable interval of the residents. In order to avoid the system only pursuing short-term completion rate, this paper further constructs the comprehensive feedback score:

$$R_{i,t} = \beta_1 c_{i,t} + \beta_2 q_{i,t} - \beta_3 f_{i,t} - \beta_4 \delta_{i,t} \tag{19}$$

Here, $c_{i,t}$ is the task completion rate, $q_{i,t}$ is the movement quality index, $f_{i,t}$ represents the degree of fatigue or high load, and $\delta_{i,t}$ represents the reminder response delay. The score also measures "whether you're doing it," "how well you're doing it," and "whether you're overdoing it," so that improved adherence doesn't just translate into increased exercise. Based on the feedback results, the resident status is updated as follows:

$$s_{i,t+1} = \Phi(s_{i,t}, g^*_{i,t}, R_{i,t}) \tag{20}$$

Here, $\Phi(\cdot)$ represents the state transition function. Thus, the system gradually learns a more suitable advice rhythm for individuals in continuous interventions, such as reducing the single time duration and increasing the frequency of reminders for people with high volatility, and increasing the intensity or extending the training period for people with stable performance.

The significance of this dynamic feedback mechanism is to change the community movement management from "unified notification" to "continuous calibration". It not only retains the group enforceability required by the public health scenario, but also realizes individual difference response through the computational model, so that the compliance improvement is based on the real behavior feedback, rather than staying at the level of experience judgment. Its overall process is shown in Figure 5.

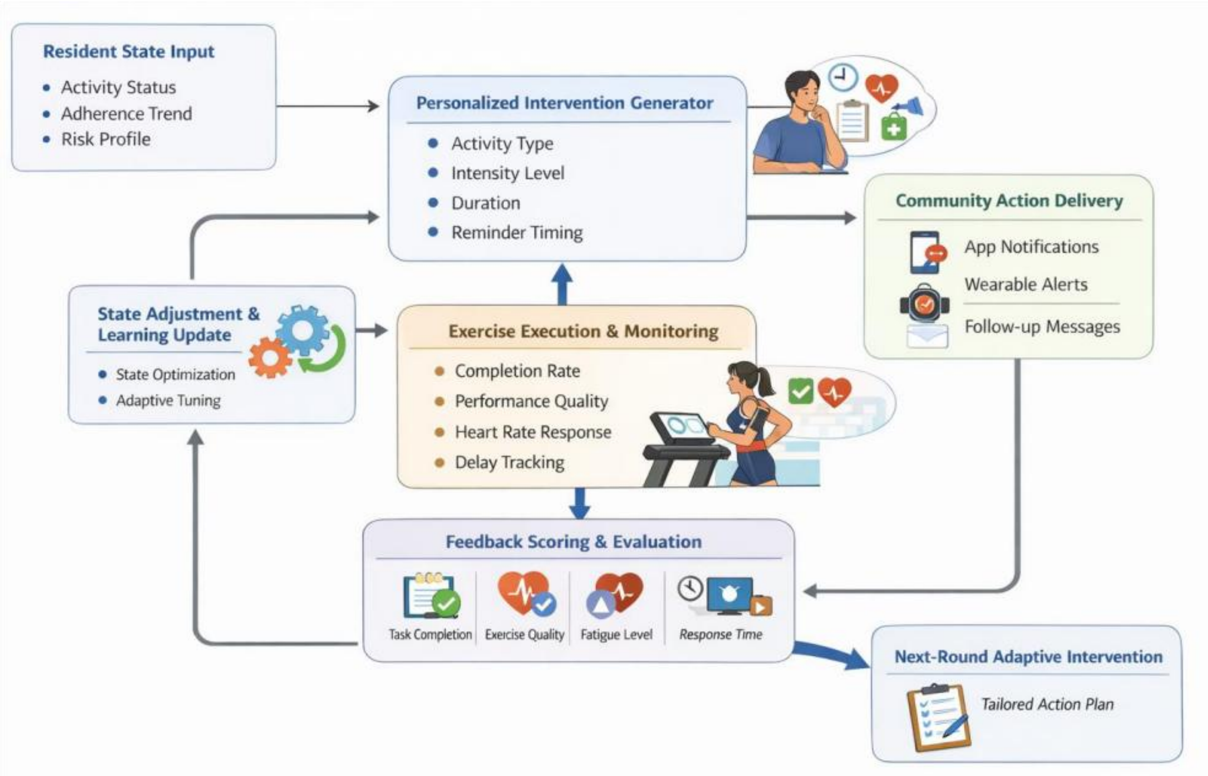

Figure 5: Framework of personalized compliance promotion and dynamic feedback mechanism

5 Results and discussion

5.1 Experimental Setup

In order to test the practical applicability of the proposed method in community public health scenarios, the experiment was carried out on three levels: "whether the behavior recognition is accurate, whether the state assessment is stable, and whether the compliance intervention is effective". The experimental data comes from the community multi-source motion monitoring samples constructed in the previous section, covering wearable device records, mobile terminal clocking logs and community follow-up information. The observation period is set to 12 weeks, and the natural week is used as the basic statistical unit to form the resident-level time series sample. After completing missing repair, time alignment and window segmentation, 3128 valid samples for modeling were finally obtained, corresponding to 428 community residents. The samples are divided into training set, validation set and test set according to 8:1:1 to ensure that the model selection and result evaluation are completed under the same data standard.

The model implementation environment is Ubuntu 22.04, Python 3.11, PyTorch 2.2, and the training hardware configuration is Intel Core i7-12700 processor with 32 GB memory. The behavior recognition module adopted the temporal coding structure, the hidden layer dimension was set to 128, the batch size was set to 64, the initial learning rate was set to 2×10^{-4}, and AdamW was selected as the optimizer. The state evaluation and feedback strategy module is jointly trained on the basis of shared representation, the number of early stopping rounds is set to 5, and the maximum number of training rounds is set to 40. In order to ensure the comparability of the results, three groups of comparison methods are set up at the same time: the first is the traditional machine learning recognition model that only uses statistical features, the second is the time series model that only performs behavior recognition without introducing resident portraits, and the third is the static intervention method that uses fixed rule push. The proposed method integrates residents' motion portrait, behavior recognition, state assessment and dynamic feedback into a unified framework.

The evaluation metrics are set separately according to the task type. For motion behavior recognition, Accuracy, Macro-F1 and Recall are used to measure the classification performance. For state evaluation, AUC and F1 were used to measure the discrimination ability. For the improvement effect of compliance, the improvement of plan completion rate, the increase of consecutive participation weeks, the decrease of reminder response delay and the change of dropout rate were focused on. The experimental process is repeated five times of independent training and averaged to weaken the interference of a single random initialization on the results. See Table 2 for the relevant configurations.

Table 2: Experimental configuration and evaluation indicators

Item	Configuration
Data Sources	Wearable signals, mobile app logs, and community follow-up records
Observation Period	12 weeks
Valid Samples	3,128 resident-level samples from 428 residents
Data Split	Training set : Validation set : Test set = 8 : 1 : 1
Runtime Environment	Ubuntu 22.04, Python 3.11, PyTorch 2.2
Hardware Configuration	Intel Core i7-12700, 32 GB RAM
Optimizer	AdamW
Initial Learning Rate	2×10^{-4}
Batch Size	64
Maximum Training Epochs	40
Early Stopping Patience	5
Comparison Methods	Traditional machine learning model, profile-free temporal model, and static rule-based intervention method
Behavior Recognition Metrics	Accuracy, Macro-F1, Recall
State Assessment Metrics	AUC, F1
Adherence Metrics	Completion rate improvement, consecutive participation weeks, response delay, and dropout rate

5.2 Analysis of exercise behavior monitoring effect

The monitoring effect of exercise behavior mainly reflects the ability of the model to recognize the real activity status of residents, and whether the recognition result can provide stable input for subsequent compliance intervention. If the monitoring layer is not reliable enough to distinguish between walking, jogging, aerobics, equipment training and resting state, subsequent state evaluation and feedback adjustment are easy to be established on the basis of bias. Therefore, this section analyzes the model from two aspects of overall recognition performance and sub-group adaptability. In this paper, the comprehensive effect of monitoring is understood as the joint embodiment of the accuracy of activity category discrimination, the balance of minority class identification and the stability of state judgment.

Table 3 shows that the proposed method is higher than the comparison model in the four indicators of Accuracy, Macro-F1, Recall and AUC. Among them, the Accuracy reaches 93.8%, which is 6.9 percentage points higher than that of the traditional machine learning model and 3.1 percentage points higher than that of the time series model without portrait. Macro-F1 is 92.4%, indicating that the model does not significantly sacrifice low-frequency activity categories. Although the traditional method using only statistical features has a certain ability to distinguish between resting and walking categories, the misjudgment rate increases significantly when facing the complex segments of fast and slow rhythm switching, short pause and instrument training. The portion-free time series model can capture continuous signal changes, so the overall performance is better than the traditional methods. However, due to the lack of resident portrait constraints, the recognition of low-intensity activities and recovery actions of elderly residents is still not stable. The static rule method performs the weakest, which is directly related to its insufficient dependence on dynamic signals.

Table 3: Comparison of locomotor behavior monitoring effects of different methods

Method	Accuracy / %	Macro-F1 / %	Recall / %	AUC
Traditional Machine Learning Model	86.9	84.7	83.8	0.887
Profile-Free Temporal Model	90.7	88.9	88.1	0.921
Static Rule-Based Monitoring Method	82.6	79.8	78.9	0.851
Proposed Method	93.8	92.4	91.6	0.956

Figure 6 further presents the Macro-F1 performance of the proposed method in different resident groups. It can be seen that the young group, middle-aged group and elderly group reach 93.1%, 92.6% and 91.4%, respectively, and the overall fluctuation is small. This shows that although the proposed model introduces multi-source features and portrait information, it is not only effective for highly active samples, but maintains good monitoring stability in different age groups. The older group had a slightly lower score, mainly because the form of exercise was more low-intensity, intermittent activity, and the boundary of some movements on the sensor signal was not as clear as that of jogging or aerobics. However, thanks to the joint modeling of state portrait and temporal context, the model can still distinguish between "light activity" and "non-motor movement", which is particularly critical for community public health scenarios. Comparison of measurement effect.

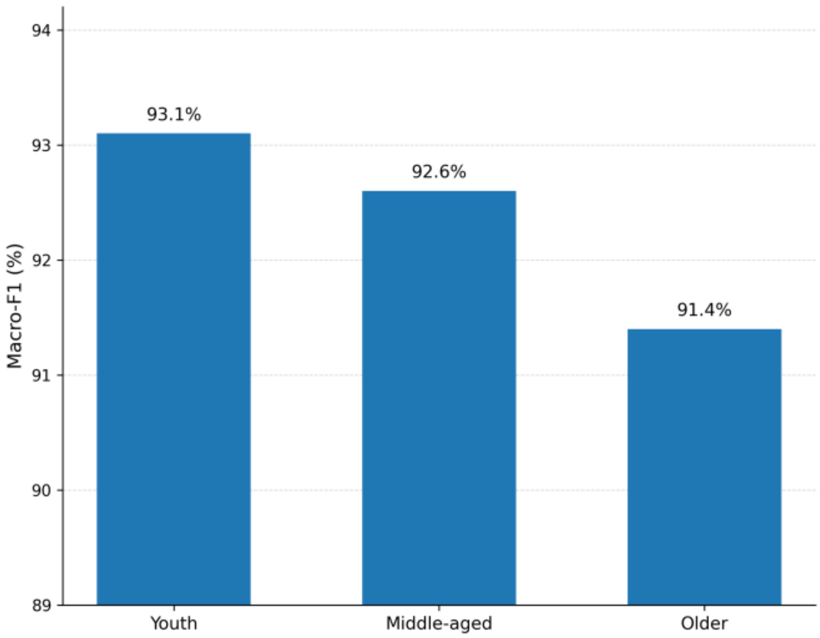

Figure 6: Motion monitoring Macro-F1 of the proposed method in different resident groups

In general, the advantages of the proposed method are not only reflected in the higher single accuracy value, but more importantly, it maintains better class balance and group stability in complex community environments. This means that the behavior labels and status results output by the monitoring module have stronger credibility, which can provide a more solid data foundation for the next compliance improvement analysis.

5.3 Analysis of physical activity and compliance improvement

The improvement of physical activity is not equivalent to simply increasing the number of exercises, but more important is whether residents can gradually form a more stable execution rhythm under the premise of acceptable load. Based on this understanding, this paper interprets compliance improvement as the improvement of activity level and implementation stability in the medium-term observation window after the system continuously modifies the recommendations according to the changes in the state of the residents. The evaluation focused on four indicators: duration of moderate to high intensity physical activity per week, plan completion rate, consecutive participation weeks, and reminder response delay. The first two reflect "do enough", the last two reflect "steady adherence".

It can be seen from Table 4 that after 12 weeks of intervention, the proposed method shows a more obvious improvement amplitude in all indicators. Compared with baseline, the duration of moderate to vigorous physical activity per week increased from 96.4 min to 158.7 min, with an increase of 64.6%. Project completion rate increased from 61.8% to 84.9%; The number of consecutive participation weeks increased from 4.2 weeks to 8.1 weeks; The average alert response delay was reduced from 5.6 hours to 2.1 hours. In contrast, although the static rule intervention also brought some improvement, the change range was significantly small, indicating that it was difficult to continuously adapt to the fluctuations in physical status, daily work and rest and execution intention of community residents only relying on fixed reminders and unified exercise suggestions. The non-portrait time series model has a certain effect on improving physical activity duration, but its plan completion rate and consecutive participation weeks still lag behind the proposed method, which indicates that relying only on behavior recognition results for feedback is not enough to form a more stable compliance improvement mechanism.

Table 4: Comparison of results of different methods on physical activity and compliance improvement

Method	Weekly Moderate-to-Vigorous Activity Duration / min	Plan Completion Rate / %	Consecutive Participation Weeks	Reminder Response Delay / h
Baseline	96.4	61.8	4.2	5.6
Static Rule-Based Intervention	121.3	70.4	5.6	4.4
Profile-Free Temporal Model	139.8	77.2	6.7	3.3
Proposed Method	158.7	84.9	8.1	2.1

Figure 7 further demonstrates the dynamics of different methods in plan completion rate over 12 weeks. It can be seen that the method proposed in this paper increases rapidly in the first four weeks, and enters a relatively stable but still continuous growth stage after the fifth week, indicating that the system can timely adjust the type, duration and reminder time of the exercise according to the early execution feedback of the residents, so as to reduce the decline in the middle. The static rule method tended to plateau after the third week, and the subsequent improvement was limited. Although the no-portrait time series model outperforms the static method, it shows slight fluctuations after the 8th week, reflecting that its response to long-term behavioral fatigue and decreased willingness to participate is still insufficient. On the whole, the proposed method not only improves the activity level of residents, but more importantly, converts this improvement into a more stable weekly performance, which is particularly critical for community public health intervention.

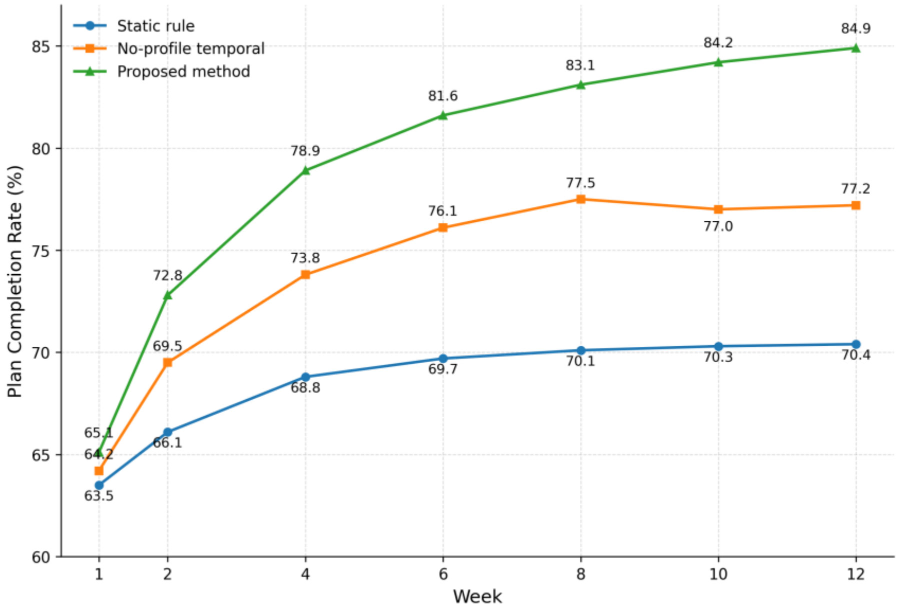

Figure 7: Change in plan completion rates for different methods in the 12-week intervention

Taking these results together, it can be seen that the advantage of the proposed method is not only reflected in the high score at a certain point, but also in the ability to continuously modify the intervention content along the change of residents 'status, and to truly translate the monitoring results into cumulative physical activity improvement and compliance improvement.

5.4 Community application evaluation and ablation analysis

In order to further judge the actual usability of the proposed method in community public health scenarios, this section continues to analyze the two dimensions of deployment effect and module contribution in addition to the above accuracy and compliance results. Community application evaluation concerns not only the level of model scores, but also whether the system can stably support residents screening, status tracking and intervention push after being connected to the community movement management process. Ablation analysis is used to answer another more specific question: to what extent the three modules of resident motion portrait, state assessment and dynamic feedback support the final effect. To this end, this paper takes the complete model as the benchmark, constructs three variants of "removing resident portrait", "removing state evaluation" and "removing dynamic feedback" respectively, and compares them under the same test set and community trial operation conditions, and the results are shown in Table 5.

Table 5: Community application evaluation and ablation analysis results

Method	Macro-F1 / %	AUC	Plan Completion Rate / %	Midway Dropout Rate / %
Full Model	92.4	0.956	84.9	8.7
Without Resident Exercise Profile	89.6	0.931	78.3	12.9
Without State Assessment Module	90.8	0.918	79.6	11.8
Without Dynamic Feedback Mechanism	92.1	0.951	74.2	15.4

It can be seen from Table 5 that the full model remains optimal in both monitoring performance and application effect. Its Macro-F1 reaches 92.4%, AUC reaches 0.956, the plan completion rate is 84.9%, and the dropout rate is reduced to 8.7%. After removing residents' portraits, the model's grasp of individual differences was significantly weakened, and the plan completion rate dropped to 78.3%, indicating that it was still difficult to cover the hierarchical differences in physical basis, sleep rhythm and past habits of community residents only relying on general behavior characteristics. After removing the state assessment, the decrease of Macro-F1 is relatively limited, but the AUC is reduced to 0.918, which reflects that although the system can still identify the action category, it is difficult to accurately determine whether the residents are currently in the stage of fluctuation, fatigue or compliance decline. After removing the dynamic feedback, the monitoring indicators changed little, the plan completion rate decreased to 74.2%, and the dropout rate increased to 15.4%, which indicated that the improvement of compliance did not automatically occur with the improvement of identification accuracy, and the continuous update of intervention content was still a key link in the formation of community application effectiveness.

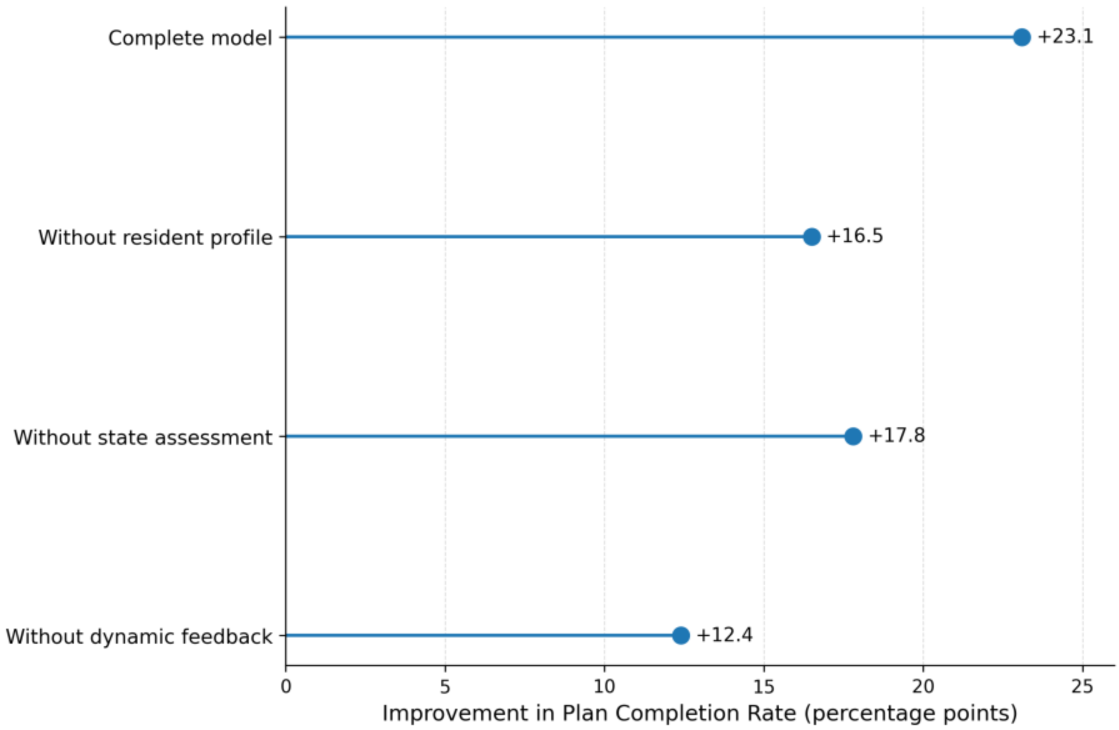

Figure 8: Improvement of plan completion rate for different schemes

Figure 8 further presents the magnitude of improvement in plan completion rate of different schemes with respect to the baseline. The full model has the most obvious improvement, reaching 23.1 percentage points. After removing resident portraits and state assessment, the improvement rate fell to 16.5 and 17.8 percentage points, respectively. After removing dynamic feedback, the improvement is only 12.4 percentage points. This is consistent with the previous results: the profiling module determines whether the system can "see who is", the state evaluation module determines whether the system can "judge where is", and the dynamic feedback mechanism directly relates to whether the system can "keep pushing suggestions to the right place". Instead of stacking them side by side, they form a continuous chain of computations.

6 Conclusions

Focusing on the problems of fragmentation of physical exercise behavior monitoring, difficulty in maintaining compliance and lagging intervention feedback in community public health, this paper constructed an intelligent analysis framework composed of multi-source data modeling, exercise portrait generation, behavior recognition and state evaluation, and personalized feedback optimization. In this study, wearable sensor signals, mobile logs and community follow-up information are incorporated into a unified representation space. After data cleaning, time alignment and feature extraction, the structured representation for residents 'continuous motion state is further formed. Based on this, the system can not only identify typical behaviors such as walking, jogging, aerobics and resting, but also make more management sense judgments on residents 'current exercise status by combining compliance trend, load change and response delay. The experimental results show that the proposed method is superior to the comparison methods in the accuracy of exercise behavior monitoring, the stability of state assessment and the improvement effect of compliance. The completion rate of the plan, the number of consecutive weeks of participation and the duration of moderate to high intensity physical activity were significantly increased, and the dropout risk was correspondingly reduced. This shows that after putting monitoring, evaluation and feedback into the same computational closed loop, community movement management can further move from "recording behavior" to "adjusting behavior", and gradually form an intervention rhythm more adapted to individual differences in the long-term implementation process. The significance of this paper is not only to propose a technology combination scheme, but also to provide a computable, traceable and updatable implementation path for daily exercise promotion in community public health. Future research can be further deepened in the aspects of cross-community transfer, online learning under weak label conditions, and finer-grained context-aware feedback, so as to further improve the generalization ability and continuous service ability of the system in real public health scenarios.

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