Research Article

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Analysis of youth sports physical health data based on cloud computing and gait awareness

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Abstract: Sub-health problems are becoming increasingly serious in today's society, and some organizations are not paying enough attention to adolescent sports health data. For adolescent sports, health needs to be measured regularly and tested constantly so that the intake of diet and medication can be reasonably adjusted according to their biochemical indicators. The Smart Health Life Growth Cloud System can effectively manage residents' health data digitally and informally, enabling users to manage their health data better and facilitating doctors to keep abreast of users' health conditions, while also facilitating the government to conduct research and studies on the physical fitness of adolescents in the areas under its jurisdiction. The cloud-based management platform for student physical health management relies on the mobile internet as a practical service platform whose primary role is to provide young people with a convenient sporting life, focusing on practicality, service, and interactivity. We also collect sensor data to detect gait patterns (with or without leg contact) and filter them through an adaptive hybrid filter to differentiate between the two patterns. In turn, the Smart Health Life Growth Cloud system changes the traditional medical model and greatly improves the information and intelligence of the healthcare industry. Using the exercise individual health evaluation model in this article is controlled to be within 20%, thus concluding that the exercise individual health evaluation model proposed in this article can predict the exercise limit of an exercise individual more accurately.

Keywords: Internet of Things, cloud computing, big data, youth, smart health, life growth

1 Introduction

The popularity and use of mobile smart terminals has increased dramatically due to the ongoing development of global mobile communication network technology, and a sizable number of mobile apps and services have developed as a carrier [1]. With the advent of the idea of "smart health," users are now able to view their own or their family's health information anytime, anywhere, using mobile communication technology and mobile applications with the assistance of mobile smart terminals nearby, and store this information in digital electronic files so they can access medical advice at any time, anywhere, for long-term, effective regulation and monitoring, and produce better results [2]. In addition, with the gradual improvement of people's living standards and the increasing demand for new medical services, portable and intelligent management devices are becoming more and more popular. The introduction of cloud computing technology has enhanced the development of information technology, making information services more widespread, as well as refining the daily needs of residents and society, allowing for the processing and analysis of large volumes of data [3].

Cloud computing and the Internet of Things have many intelligent applications, and research practice shows that the data generated during youth sports exercise not only reflect the real spatiotemporal activity trajectory of the

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exerciser but also contain rich and valuable information related to the whole exercise process [4]. In the process of exercise, data such as exercise time, speed, acceleration, step count, and energy consumption can be generated, among which exercise energy consumption can reflect the two key data of exercise volume and exercise intensity of the exerciser, so exercise energy consumption is the most reflective data of exercise [5]. Therefore, through real-time monitoring of energy consumption during exercise, we can grasp the exercise volume and intensity of the exerciser in time, and the exercise monitor can guide and adjust the exercise of the exerciser according to the actual situation to achieve a more reasonable and healthy exercise effect [6]. In addition, through real-time monitoring of the energy consumption of the exerciser, it is possible to detect any possible accidental conditions that may occur during the exercise process due to over-exercise, and with the corresponding alarm mechanism, it is possible to achieve risk control in the exercise process and minimize the occurrence of tragedies during the exercise process.

Physical exercise is often group-based, i.e., sportspeople participate in planned, organized, and purposeful physical activities according to their needs, interests, and individual characteristics, to achieve the most suitable effect for their physical health development [7]. However, due to the influence of the current examination-based education, in the reality of physical education activities, the development of sports programs and plans are done by the school or physical education teachers and are implemented for all students. The counseling approach used by physical education instructors improves the effectiveness of public education by offering expert advice, individualized fitness programs, goal setting, nutritional assistance, motivation, injury prevention, tailored exercises, community engagement, and routine evaluations. As a result, students rarely have the energy and opportunity to participate in the sports they are interested in, and gradually lose interest in sports and exercise, which is only a formality and not intense enough, making it difficult to achieve the best results in sports and exercise. To address the above problems, by analyzing the movement data obtained from real-time monitoring during the exercise of sportsmen and extracting the movement characteristics of sports individuals, it is possible to discover the implied laws in the process of sports exercise [8]. By analyzing data on the number of steps taken, time spent in exercise, exercise items, and energy consumption, a health evaluation model can be constructed for the exercise process of an individual, which can provide a personalized evaluation of the exercise effect, exercise tolerance and improvement in physical fitness of the individual, thus achieving the goal of providing personalized guidance such as differentiated treatment and graded teaching for the individual. Research possibilities are restricted, health inequities, missing health concerns, and a lack of responsibility might result from the absence of juvenile physical fitness assessments in national health policies. Using standardized fitness testing to promote juvenile health and well-being is important. Furthermore, by combining the health data of individual sportsmen, such as height, weight, age, gender, and personal health status, a health evaluation model can be constructed for sports groups, eliminating the influence of individual differences on the health evaluation of the group and providing a fair and objective evaluation of the overall exercise effect of sports groups, thus helping schools or physical education teachers to arrange sports exercise scheme reasonably [9].

Through the real-time monitoring of exercise data, the exercise monitor can grasp the real-time situation of exercisers' exercise in a timely and effective manner, thus realizing real-time intervention and guidance of the exercise process [10]. By analyzing the data obtained from exercise monitoring, combined with the physical health indicators of exercisers, the exercise health evaluation model can be constructed, which can achieve the health evaluation of exercise individuals and groups, and achieve the purpose of personalized guidance for exercisers and judging the overall exercise effect of exercise groups [11]. Based on the construction of an online service platform for youth health evaluation and sports intervention in cooperation with the Key Laboratory of the Ministry of Education, the research has a certain application basis and good research prospects [12].

2 Physical health promotion management

2.1 Physical health management in a cloud management model

Cloud-based management platform for student physical health management relies on the mobile internet as a practical service platform, the main role is to provide a convenient sports life for many young people, with a focus on practicality, service, and interactivity [13]. Preventive healthcare, emergency preparation, and centralization of health information are all made possible by a cloud-based platform for managing physical health among students. It involves parents in their child's health and simplifies reporting and administrative duties. The platform seeks to improve the well-being of students. Youth physical health promotion cloud management mainly includes the management body and the management module. First, the cloud management platform establishes a "four-in-one" management model for students, physical education teachers (class teachers), schools, and authorities to promote the management and sharing of student physical health information (Figure 1). A better, more knowledgeable attitude to physical well-being is promoted when students receive feedback on their physical health. This enhances awareness, motivation, goal setting, education, self-reflection, and self-efficacy, as well as preventing health complications. Based on the evaluation system of the National Standard for Student Physical Fitness, the "verification (monitoring), evaluation, early warning, feedback (information, online platform) and intervention" physical fitness promotion system is established from the perspective of five interlinked and coordinated mechanisms: verification (monitoring), evaluation, early warning, feedback, intervention, and verification (monitoring). The core functions of this dynamic system are in three areas: student physical health data management, student physical health assessment (early warning), student physical health assessment, and student physical health decision-making (profile).

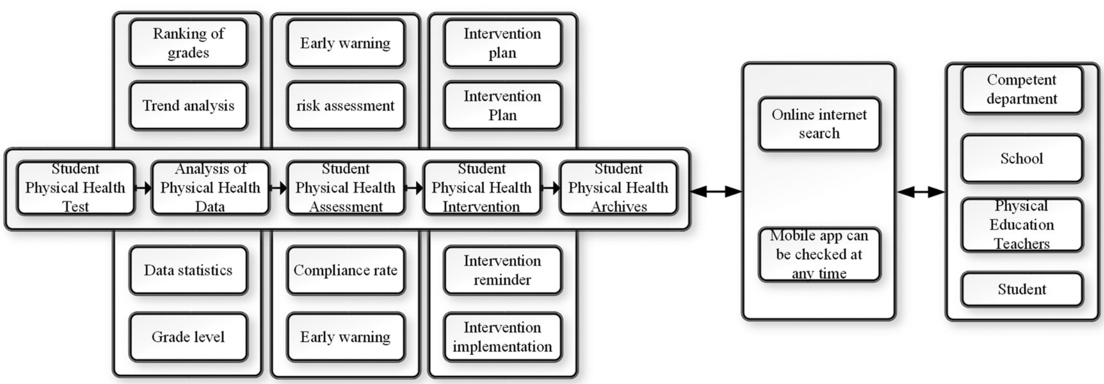


Figure 1: Cloud-based management platform for physical health management system.

In the "Cloud Management Platform + Student Health" model, the data and information processing functions of the cloud platform are fully utilized. Cloud solutions increase the effectiveness of physical health testing by centralizing health data, providing scalability, security, and user-friendly interfaces, and enabling real-time monitoring, automated analysis, remote tracking, and efficient reporting. Scalability, affordability, accessibility, big data analytics, artificial intelligence, disaster recovery, real-time processing, global reach, application programming interfacs, quick application development, data insights, sustainability support, and innovation are all provided by cloud-based data processing. On the one hand, it enhances the timeliness, efficiency, and convenience of overall physical health testing and student health services. On the other hand, it provides a new way of working for managing student health information, making the management of student health more comprehensive and providing alerts and targeted measures for weaknesses in student health.

2.2 Pathway of youth physical health promotion under the cloud management model

The early warning of student physical health is mainly based on the assessment of the National Student Physical Fitness Standard levels, based on student physical fitness test results, a systematic evaluation of adolescent physical fitness test results, and a method to judge the total score (level) of student physical fitness and the unevenness of individual physical fitness and make corresponding early warning warnings [14]. In early warning systems for physical fitness, students are motivated by prompt feedback, concerns identified, goals set, tailored recommendations, health awareness promoted, parents and educators involved, progress tracked, accountability instilled, rewards offered, and positive role models displayed. Informed lifestyle choices are supported, and educators, parents, and legislators may use the data obtained from the assessment of NSPFS levels to inspire kids, improve academic achievement, avoid illnesses, and promote physical health.

The construction of an early warning mechanism for students' physical fitness consists of two main components (Figure 2). First, based on the requirement of "good or above to participate in the awarding of prizes and merits" in the Standards, an early warning is given to the total score (grade) of students' physical fitness, and the scores in the "pass" and "fail" stages are given an early warning. The second is the unbalanced warning of individual student indicators, where the warning is about the "weaknesses" of individual student indicators. The second is an unbalanced warning for individual indicators, which is a "weakness," i.e., a "pass" or a "failure" for individual physical form, physical function, and physical fitness indicators, representing "level 1 warning" and "level 2 warning," respectively. To identify at-risk kids and offer the appropriate help, early warning systems for students rely on several factors, such as performance benchmarks, historical comparisons, and standardized exams, "Level 1 warning" and "Level 2 warning," respectively. As the physical condition of students varies from region to region, so do the values set in the Standards when setting early warning parameters for student fitness (Table 1) [15]. When students' physical fitness test scores fall below the defined values in the Standards, feedback is given to students, physical education teachers, class teachers, and schools to raise students' awareness of their physical fitness status and to urge them to exercise in a targeted manner, to improve students' physical fitness.

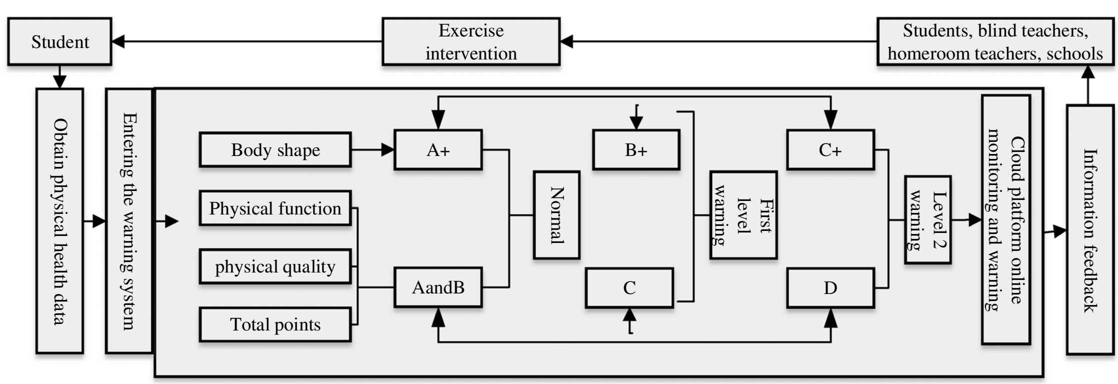


Figure 2: Youth physical health warning model. (Note: "A+", "B+", "C+" represents "normal," "low weight and overweight," and "obesity" in the BMI index; "A+", "B+", "C+", "D+" represents the "excellent," "good," "pass," and "fail" levels in the standard.)

Fundamentally, a single level of warning cannot serve the true purpose of a student's physical health warning, and only students can become more conscious of their physical health when they are genuinely aware of the status of their bodies at the moment and any potential hazards [16]. This is why it is important to develop a feedback form for physical health warnings. Physical health warning feedback forms enable user engagement, quality enhancement, data collecting, personalized messaging, risk detection, insights into user behavior, empowerment, policy formulation, accountability, and public health results. The focus of the

Table 1: Threshold of physical health prediction parameters for adolescents

Type	Index	Male threshold		Female threshold		Grade
		Freshman and sophomore	Junior and senior	Freshman and sophomore	Junior and senior	
Body shape	BMI index (kg/m^2)	≤17.9	≤17.2	≤17.2	≤17.2	Low body weight
		24.1–28.0	24.1–28.0	24.1–28.0	24.1–28.0	Overweight
		≥28.1	≥28.1	≥28.1	≥28.1	Obesity
Physical function	Vital capacity (ml)	3,101–4,300	3,201–4,400	2,001–3,000	2,051–3,050	Pass
		≤3,100	≤3,200	≤2,000	≤2,050	Fail
	50 m run (s)	7.3–9.2	7.2–9.1	8.5–10.4	8.4–10.3	Pass
		≥9.3	≥9.2	≥10.5	≥10.4	Fail
	Sitting forward flexion (cm)	3.8–17.7	4.3–18.2	6.1–19.0	6.6–19.5	Pass
		≤3.7	≤4.2	≤6.0	≤6.5	Fail
Physical quality	Standing long jump (cm)	209–248	211–250	152–181	153–182	Pass
		≤208	≤210	≤151	≤152	Fail
	Pull-ups/sit-ups (reps)	11–15	12–16	27–45	28–47	Pass
		≤10	≤11	≤26	≤27	Fail
	800 m/1,000 m (min s)	3.44–4.33	3.42–4.31	3.46–4.35	3.44–4.33	Pass
		≥4.34	≥4.32	≥4.36	≥4.34	Fail
Total points	Indicator and (score)	61–80	61–80	61–80	61–80	Pass
		≤60	≤60	≤60	≤60	Fail

feedback form is to explain the content of the student's warning level (Table 2) and to provide feedback to students and physical education teachers in the form of a "profile" [17]. On the one hand, the feedback form allows students to know exactly where they are in terms of their fitness indicators and to use the early warnings as a basis for targeted practice to strengthen their "weak" indicators. The feedback on students' physical health information strengthens the students' perception of their physical condition, thus creating a sense of urgency at the psychological level and prompting students to re-examine the results of their physical health assessment and engage in physical activity accordingly. On the other hand, physical education teachers can provide targeted counseling and contact with students based on their early warning tips, which not only improves the efficiency of public physical education classes but also ensures the improvement of students' overall physical fitness level.

By following up on the results of youth physical fitness tests in recent years, we found that youth physical fitness tests have not been improved under the guidance of the national physical health policy; the main reason for this is that although youths can know the items in which they are deficient in physical fitness tests during their four years in university, they should make corresponding exercises to improve these items but are very vague, and some students have insufficient knowledge of physical education and related sports. Several reasons, including insufficient curriculum, socioeconomic inequalities, cultural influences, gender inequities, physical and health problems, limited exposure, peer pressure, digital diversions, and language obstacles, contribute to kids' lack of understanding about physical education and sports. Some students do not have sufficient knowledge of sports and related exercises, which leads to the inability of young people to choose the right sports to improve their physical fitness [18]. Therefore, the physical health management department of universities should formulate exercise prescriptions according to the physical health test results of youths to guide youths to carry out physical exercises in a planned and targeted manner. Through interviews with experts from the Soochow University Physical Fitness Test Centre and surveys of trainers working in the fitness industry, exercise prescriptions for youth physical fitness programs were developed (Table 3) to provide a theoretical reference for youth to exercise in a more targeted manner [19].

Table 2: Feedback form of youth physical health prediction information

Type	Index	Warning level	Warning prompt
Body shape	BMI index	First level warning	Low body weight
		First level warning	Overweight
		Level 2 warning	Obesity
Physical function	Vital capacity	First level warning	The cardiopulmonary function is average, and the body's ability to absorb oxygen and eliminate exhaust gases is average
		Level 2 warning	Poor cardiopulmonary function, poor ability of the body to absorb oxygen and eliminate exhaust gases
	50 m run	First level warning	Speed, agility, and other qualities are average
		Level 2 warning	Poor speed, agility, and other qualities
	Sitting forward	First level warning	Moderate flexibility
		Level 2 warning	Poor flexibility
Physical quality	Standing long jump	First level warning	Lower limb explosive power and body coordination ability are average
		Level 2 warning	Poor explosive power and physical coordination in lower limbs
	Pull up	First level warning	Upper limb strength is average
		Level 2 warning	Poor upper limb strength
	Abdominal curl	First level warning	Abdominal muscle endurance is average
		Level 2 warning	Poor abdominal muscle endurance
	800 m/1,000 m	First level warning	Cardiovascular respiratory system and muscle endurance are average
		Level 2 warning	Poor cardiovascular respiratory system and muscle endurance
Total points	Indicators and	First level warning	Their physical health and overall quality are average, unable to participate in awards and evaluations
		Level 2 warning	Poor physical health and overall quality, unable to participate in awards and evaluations

Note: The warning information feedback form is formulated based on the "National Student Physical Health Standards" and warning parameters.

3 Research methodology for gait recognition

As shown in Figure 3, the sensor data collected were used to detect gait patterns (with or without leg contact) and filtered by adaptive hybrid filter (AHF) to differentiate between the two patterns. The need for AHF filtering in gait identification relies on several parameters, including machine learning methodologies, processing capacity, and data quality. Therefore, its applicability must be carefully assessed. Based on these two modes (support and jump), the acceleration double integration and layered information are used to estimate the centroid displacement [20].

3.1 Analysis of the running model

To estimate the displacement of the mass, the gait cycle of the running process should first be analyzed. Running gait cycle analysis has several advantages, such as biomechanical understanding, injury avoidance, improved performance, rehabilitation assistance, tailored treatments, diagnosis, research, patient education, and data-driven tracking. It is understood that the running process consists of two main parts: one is the support period, and the other is the leap period [21]. When it comes to running biomechanics, researching

Table 3: Statistical table of exercise prescription intervention in adolescent physical health test items

Type	Index	Exercise prescription intervention content
Body shape	Low body weight	Morning running, brisk walking, cycling, half-sleeping, dancing, walking, bowling, etc.
	Overweight/obesity	Running, brisk walking, jogging, badminton, table tennis (noncompetition), swimming, fitness equipment, etc.
Physical function	Vital capacity	Rope skipping, games, aerobics, walking on the flat, jogging on the flat, fitness running platform, fitness bicycle, etc.
	50 m run	Dumbbell arm swing, reverse acceleration run, small step run, 50 m variable speed run, badminton, table tennis (competition confrontation), etc.
	Sitting forward flexion	Tai Chi, yoga, gymnastics, lunge walking, lunge leg pressure, crawl leg pressure, hurdle step leg pressure, etc.
Physical quality	Standing long jump	Mountaineering, high leg lifting, skipping rope, jumping steps, backstepping, squatting, frog jumping, weight lifting, football, roller skating, deep jump, etc.
	Pull up	Double rock jump rope, push-ups, handstands, dumbbell flat lifts, barbell oblique push, large flying birds, parallel bar support pendulums, basketball, volleyball (entertainment), etc.
	Abdominal curl	Plank, sit-ups, supine leg lifts, hanging leg lifts, supine cross turns, side lying leg lifts, etc.
	800 m/1,000 m	Mountaineering, morning running, brisk walking, 100-m variable speed running, power cycling, swimming, variable speed running, badminton (noncompetitive), etc.

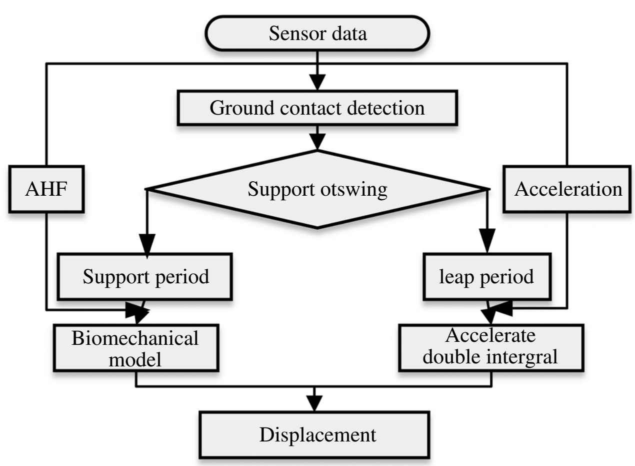
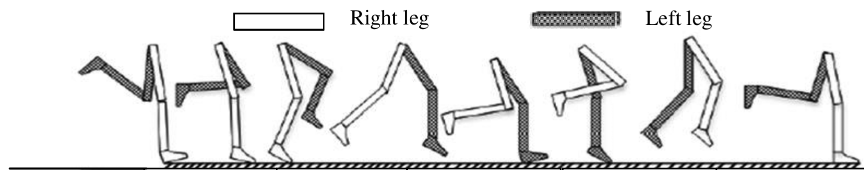


Figure 3: Algorithm framework.

human gait may help with clinical diagnosis, reduce the risk of injury, improve performance, tailor training, promote biomechanical research, offer data-driven insights, and improve coaching and instruction. Figure 4 shows the sequence of movements of the left and right legs of the human body over some time.

According to the different states of the left and right legs, the support period can be divided into two processes: (i) left side support, right side swing; (ii) right side support, left side swing. During running, the left and right legs swing alternately. Running with alternate leg swings enhances forward motion, stability, balance, energy conservation, coordination, endurance, and injury avoidance. It improves running as a technical skill, performance, and mind-body connection. To obtain the displacement of the human body during running, it is necessary to detect the gait pattern and then adaptively apply different displacement estimation methods. Precise displacement estimation in running improves biomechanical insights, injury avoidance, pace, training efficiency, and performance monitoring. It also supports sports science research, motivation, and decision-making.



Process label	Process 1	Process 2	Process 3	Process 2	Process 1
Human state	Support period	Leap period	Support period	Leap period	Support period
Right leg state	Support period	Swinging leg			
Left leg state	Swinging leg		Support period	Swinging leg	

Figure 4: Movement sequence of left and right legs.

3.2 Algorithm for centroid displacement during support period

During the support phase, displacement is calculated from the extension and flexion angles of the lower body joints. Figure 5 shows the course of the body movement in the XOY plane view.

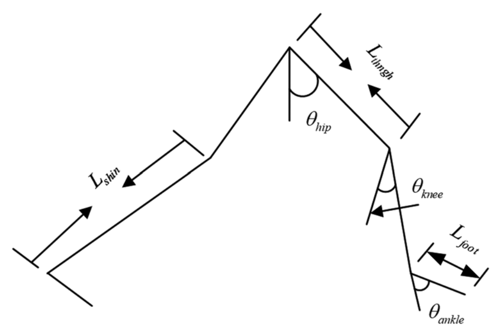


Figure 5: The process of human motion on the XOY plane view.

When in a running phase, we use stratification information to estimate displacement. For an accurate estimate of displacement, one must take into account a variety of elements, including geography, weather, impediments, human factors, measuring techniques, time constraints, instruments, outside effects, and data sources. As mentioned above, the root refers to the vector sum of the lengths of the foot, thigh, and knee. As shown in equations (1) and (2):

$$S^x_{\text{root}} = S^x_{\text{thigh}} + S^x_{\text{shin}} + S^x_{\text{foot}}, \tag{1}$$

$$S^y_{\text{root}} = S^y_{\text{thigh}} + S^y_{\text{shin}} + S^y_{\text{foot}}. \tag{2}$$

$S^x_{\text{foot}}S^x_{\text{thigh}}S^x_{\text{root}}S^x_{\text{shin}}$ represent the vectors on the *X*-axis for the root, thigh, calf, and foot, respectively, $S^y_{\text{root}}S^y_{\text{thigh}}$, S^y_{shin}, S^y_{foot} represent the vectors up the *Y*-axis for the root, thigh, calf, and foot, respectively.

$$\begin{aligned} S_i^x &= L_k \sin(\theta_{i,t+\Delta t}) - L_k \sin(\theta_{i,t}) \\ S_i^y &= L_k \cos(\theta_{i,t+\Delta t}) - L_k \sin(\theta_{i,t}). \end{aligned} \tag{3}$$

S_i^x, S_i^y is the change on the $t + \Delta t$ axis from cycle t to X, Y. L_k is denoted as the length of joint K, $\theta_{i,t+\Delta t}$ is the angle at time $t + \Delta t$ node, and $\theta_{i,t}$ is denoted as the angle at time t node. At time $t + \Delta t$, the expression for the root is shown in equation (4):

$$\begin{aligned} S^x_{\text{root},t+\Delta t} &= S^x_{\text{root},t} + S^x_{\text{root},t} \cos(\theta_{\text{root}}) \\ S^y_{\text{root},t+\Delta t} &= S^y_{\text{root},t} + S^y_{\text{root},t} \sin(\theta_{\text{root}}). \end{aligned} \tag{4}$$

$S^x_{\mathrm{root},t+\Delta t}$, $S^y_{\mathrm{root},t+\Delta t}$ are represented as the root vector on the X and Y axes at the time node of $t + \Delta t$ and θ_{root} is the angle of the root vector.

3.3 Algorithm for estimating the displacement of the mass in the fly-over period

During the leap period, human motion is only influenced by gravity. Based on Newtonian kinematics, at time node $t + \Delta t$, the root node $S^k_{\mathrm{root},t+\Delta t}$ has the following equation:

$$S^k_{\mathrm{root},t+\Delta t} = S^k_{\mathrm{root},t}(\upsilon_k + 0.5 \times a^k_{t-1})\Delta t. \tag{5}$$

$S^k_{\mathrm{root},t+\Delta t}$ is denoted as the root vector of the K axis at time node $t + \Delta t$, υ_k is the velocity of the root vector that can be solved by integration with a gyroscope, and a^k_{t-1} is denoted as the integration over the K axis of one of the three axes.

4 A study of health evaluation models for exercising individuals

Exercise is a stochastic process, and therefore, a Markov model can be used to describe the exercise process. When evaluating an individual's health over time, a Markov model is utilized to track the influence of exercise and other factors. Based on the idea of memorylessness, it facilitates the computation of quality-adjusted life years and the assessment of health policies and initiatives. We can assume that the stability of Markov chains can be used to predict the future exercise state of an exercising individual under the premise that his or her physical strength remains stable, which can eliminate the influence of individual basal differences and yield a stable exercise state of the exercising individual, thus making an exercise health evaluation of him or her [22]. In Markov models, a sensible setting for discretization, granularity, exercise patterns, flexibility, monitoring intensity, and data availability is to set the energy expenditure rate for workouts at 30 s.

4.1 Exercise individual health evaluation model

The exercise energy expenditure data collected in the real-time exercise data monitoring system is collected at a frequency of once per second. Because data per second exhibits minimal variation, and data may be intermittently missing at specific seconds due to network conditions. For analysis, the collected exercise energy expenditure data is converted into exercise energy expenditure (in kcal/30 s) every 30 s, which is called the exercise energy expenditure rate and is denoted as $r_n (n = 1, 2, 3, \ldots)$. In the exercise individual health evaluation model, network problems might result in biased data, lower accuracy, and incomplete evaluations. For a model to be effective, reliable data transmission and gathering methods must be included.

In the process of exercise, as the exercise time advances, the physical exertion of the exerciser first gradually increases and then reaches a relatively stable state, as the human physical strength is limited and finally decreases, the corresponding energy consumption rate will show a gradual increase and then a steady and finally decreasing. On the premise that the exercise state is stable, according to the stability of the Markov chain, we can predict the exercise limit energy consumption rate of 0. If we find that the exercise rate reaches this limit of 0, we can remind the exerciser to reduce the exercise intensity or stop exercising, to achieve the purpose of health evaluation of the exercise individual.

To predict the limiting energy consumption rate of a moving individual based on a Markov model, the current real-time monitored energy consumption of the movement can be calculated to obtain a sequence of energy consumption rates $r_1, r_2, \ldots r_n$. The steps of the Markov process for analyzing this sequence are as follows:

(1) Divide the state space, the state intervals of the energy consumption rate sequence are divided as follows:

$$[r_{\max},\ r_{\min} + \Delta r], \ldots ,[r_{\min} + (m - 1)\cdot \Delta r,\ r_{\max}]. \tag{6}$$

(2) Calculate the transfer probability matrix. Analysis of the energy consumption rate state transfer for each successive 30 s (e.g., state transfer from the 30th to the 60th) and calculation of the transfer probability matrix for the energy consumption rate P_r;

(3) Find the steady state vector. Using the state of the energy consumption rate at the 30th s as the initial state. In a Markov chain model, the steady-state probability vector – which represents equilibrium distribution and long-term health outcomes – is essential for exercise and health assessment. It helps with model calibration, health forecasting, and policy assessment. Note that this initial state vector is S_n, then the following equation holds:

$$S_{n+1} = S_n \cdot P_r,\ S_{n+2} = S_{n+1} \cdot P_r, \ldots , \tag{7}$$

$$Q = \sum_{1}^{m} R_i \cdot s_i. \tag{8}$$

5 Example analysis

5.1 Health evaluation

The health evaluation model for youth sports individuals uses a health evaluation model based on the exercise energy expenditure rate, which aims to calculate the exercise limit energy expenditure rate Q of the sports individual and to evaluate the health of the individual [23,24]. Numerous techniques, including VO2 max, heart rate monitoring, functional capacity evaluation, wearable fitness trackers, and self-reports, are used in the assessment of health based on exercise limit energy expenditure rate. Calculating the basal metabolic rate, physical activity level, total daily energy expenditure, and resting energy expenditure yields the exercise limit energy expenditure rate. With the use of indirect calorimetry for accurate readings, it is dependent on personal aspects as well as expert advice.

The following is based on the energy expenditure data of an exerciser in a continuous real-time exercise to evaluate this exerciser's health [25]. The exercise data real-time monitoring system may collect the exercise energy expenditure data of all exercise persons in real-time. Enhancing fitness journeys and user pleasure, a workout data real-time monitoring system offers real-time feedback, performance tracking, safety monitoring, customization, compatibility, user engagement, analytical insights, goal attainment, and support. The energy expenditure rate is set to equal the workout energy expenditure every 30 s to simplify the subsequent analysis and calculation. The energy expenditure rate of a certain exerciser over 10 min is shown in Table 4.

According to the formula, the above energy consumption rate is divided into four state spaces, i.e., $m = 4$, then $\Delta r = (7.208 - 2.688)/4 = 1.130$, at which point the state space (noted as states A, B, C, D in that order) is divided as follows:

$$A = [2.688,\ 3.818),\ B = [3.818, 4.948),\ C = [4.948,\ 6.078),\ D = [6.078,\ 7.208]. \tag{9}$$

Based on the above division of the state space, the energy consumption rate transfer statistics for two adjacent 30 s can be derived, as shown in Table 5.

According to the data in Table 5, the transition probability matrix can be obtained as follows:

$$P = \begin{bmatrix} 1/2 & 1/2 & 0 & 0 \\ 1/8 & 5/8 & 1/4 & 0 \\ 0 & 2/5 & 2/5 & 1/5 \\ 0 & 0 & 1/4 & 3/4 \end{bmatrix}. \tag{10}$$

Table 4: Energy expenditure rate of a certain athlete

Time (s)	Energy consumption rate (kcal 30 s)	Time (s)	Energy consumption rate (kcal 30 s)
30	3.643	330	6.296
60	4.018	360	7.209
90	3.947	390	6.864
120	4.130	420	5.922
150	4.137	450	4.499
180	5.689	480	4.033
210	5.744	510	3.824
240	4.288	540	4.026
270	5.729	570	3.122
300	6.825	600	2.689

Table 5: Statistics of adjacent energy consumption rate transfer

Number of transfers		After transfer				Amount to
		A	B	C	D	
Before transfer	A	0	0	1	1	2
	B	2	4	1	1	8
	C	1	2	2	0	5
	D	0	0	2	2	4

Next, using the state at 600 s (minute 10) as the initial state, i.e., $S_n = (1, 0, 0, 0)$, the ensuing rate of energy consumption can be predicted according to the equation $S_{n+1} = S_n \cdot P$.

The probability vector in the steady state, i.e., the stable vector S of this Markov chain, is required to satisfy $S = S \cdot P$, i.e., $(E - P^T)\cdot S^T = 0$. It can be seen that to obtain the stable vector S, it is sufficient to obtain the transpose matrix P^T of the transfer probability matrix P with eigenvalues of 1 as eigenvector $X_n = (x_1, x_2, x_3, x_4)$, and to obtain the eigenvector X_n, which is listed in the characteristic equation as

$$\begin{cases} -\dfrac{1}{2}x_1 - \dfrac{1}{8}x_2 = 0 \\ -\dfrac{1}{2}x_1 + \dfrac{3}{8}x_2 - \dfrac{2}{5}x_3 = 0 \\ -\dfrac{1}{4}x_2 + \dfrac{3}{5}x_3 - \dfrac{1}{4}x_4 = 0 \\ -\dfrac{1}{5}x_3 + \dfrac{1}{4}x_4 = 0. \end{cases} \tag{11}$$

System analysis relies heavily on the steady-state probability vector for a Markov chain, which is derived by multiplying the transition matrix by the starting probability vector [26]. This vector reveals the long-term behavior of the Markov chain. Since the underlying solution system for this characteristic equation is

$$\xi = \left(\frac{2}{5}, \frac{8}{5}, 1, \frac{4}{5}\right). \tag{12}$$

The equation has no unique solution, which can be obtained by adding the constraint $\sum_{i=1}^{4} x_i = 1$, which is the stable vector S, i.e., the stable vector:

$$S = \left(\frac{2}{19}, \frac{8}{19}, \frac{5}{19}, \frac{4}{19}\right). \tag{13}$$

From the resulting stability vector S, the limiting rate of energy expenditure Q can be found for the exerciser

$$Q = 3.818 \times \frac{2}{19} + 4.948 \times \frac{8}{19} + 6.078 \times \frac{5}{19} + 7.208 \times \frac{4}{19} = 5.602 \tag{14}$$

As illustrated in Figure 6, we may plot based on this exercise limit energy consumption rate and the exerciser's energy consumption rate for each period to determine the constant energy of the exerciser in the current exercise condition. The consumption rate is 5.602 kcal/30 s.

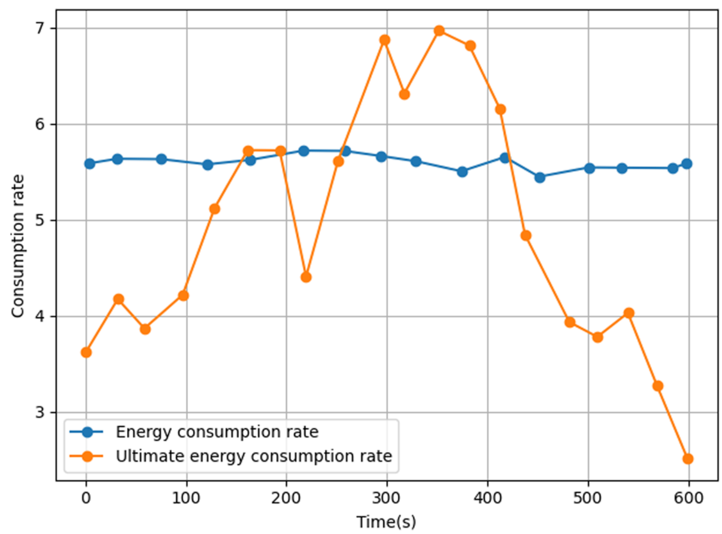


Figure 6: Comparison of energy expenditure rate and ultimate energy expenditure rate of a certain athlete during continuous 10 min of exercise.

Figure 6 shows that the exerciser's energy expenditure rate starts to drop below the maximum rate of 5.602 kcal/30 s at about the 450-s mark and keeps dropping throughout the exercise, indicating a loss of physical strength.

5.2 Comparative validation

To evaluate the accuracy of the findings of the exercise individual health evaluation model, 20 exercisers were selected to participate in a 2 km run, and the exercise data was monitored using a real-time exercise data monitoring system [27]. The actual exercise time T was obtained when the exercisers felt physically exhausted during the exercise process

$$E\frac{|T_0 - T|}{T}. \tag{15}$$

The threshold of error E_{Th} is set; if the error is within the value of E_{Th}, the evaluation result is considered correct; otherwise, the evaluation result is incorrect. The accuracy of this health evaluation model can be judged by combining the overall correctness of these 20 exercisers.

The error produced by the exercise individual health evaluation model for each exercise individual may be determined using the test result data in Table 6; the error is then plotted, and the results are displayed in Figure 7. The exercise-stopping time predicted using the exercise individual health evaluation model in this article was within 20% of the actual exercise-stopping time, as shown by the graph, for all 20 study participants. Even after accounting for the influence of arbitrary human factors, the model's prediction results' inaccuracy is still within a tolerable range. A key component in evaluating the correctness of a model is the error threshold (E_{Th}), which establishes the permissible degree of inaccuracy between forecasts and actual observations while also influencing complexity, sensitivity, and precision. If the error threshold E_{Th} is set at

Table 6: Actual exercise and recommended exercise time

Athlete ID	Actual exercise time T(s)	Suggested exercise time T_0(s)
1	622	600
2	674	630
3	703	660
4	649	600
5	730	690
6	609	570
7	731	630
8	598	630
9	583	600
10	659	630
11	693	720
12	644	600
13	687	570
14	624	600
15	668	690
16	719	660
17	621	570
18	640	690
19	638	630
20	673	600

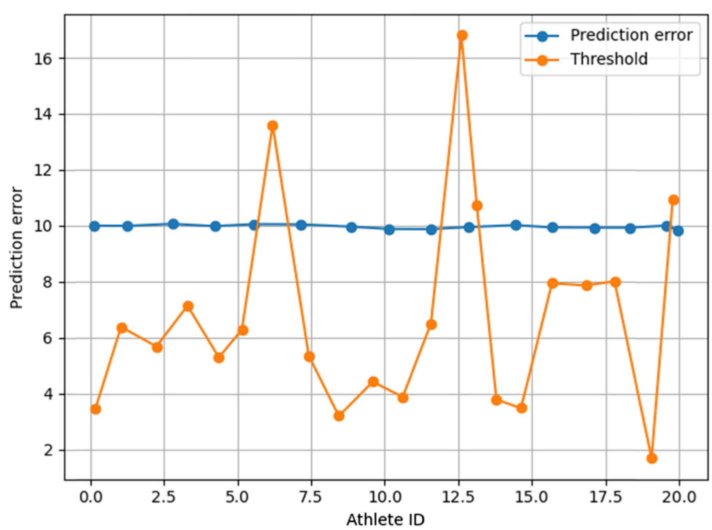


Figure 7: Error chart of the recommended time and actual time of the health assessment model for 20 athletes.

10%, then the accuracy of this test is 85%, which is quite satisfactory. It can be concluded that the health evaluation model proposed in this article can predict the exercise limit of the exercise individual more accurately and give reasonable exercise advice.

5.3 Health evaluation model

Based on the analysis in the preceding section, a group health evaluation model based on the degree of progression of exercise energy expenditure transfer is used for the exercise health evaluation of exercise groups. A group's health is evaluated using a model that takes into account social determinants, lifestyle decisions, environmental impacts, and individual health measures. It pinpoints risk factors, health trends, and development opportunities. This model allows for the degree of improvement of exercise effect between exercise groups in the same period, concluding the exercise health evaluation of exercise groups.

Based on data obtained during two consecutive weeks of real-time exercise in both classes of A, B, Tables 7 and 8 show the average weekly exercise energy expenditure for each exercising individual.

Tables 7 and 8 show the average weekly exercise energy expenditure data (in kcal) for all exercising individuals within classes A, B during two consecutive weeks of real-time exercise, respectively.

Table 7: Average weekly exercise energy expenditure of all individuals in Class A during two consecutive weeks of real-time exercise

Sports individual number	**1**	**2**	**3**	**4**	**5**	**6**
Average energy consumption in week 1	372.75	453.58	394.58	381.52	408.06	479.46
Average energy consumption in the second week	408.95	425.12	439.48	405.15	471.19	428.46
Sports individual number	7	8	9	10	11	12
Average energy consumption in week 1	348.33	520.0	456.96	415.54	504.29	402.8
Average energy consumption in the second week	397.52	491.52	396.64	437.64	504.29	423.64

Table 8: Average weekly exercise energy expenditure of all individuals in Class B during two consecutive weeks of real-time exercise

Sports individual number	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Average energy consumption in week 1	251.24	236.29	298.19	275.26	320.32	308.22	273.75
Average energy consumption in the second week	265.13	251.92	271.63	281.22	331.13	327.44	258.26
Sports individual number	8	9	10	11	12	13	14
Average energy consumption in week 1	265.22	323.46	319.22	286.43	266.39	376.32	252.22
Average energy consumption in the second week	273.54	348.13	323.83	261.38	289.32	263.25	289.47

Divide all the average energy consumption of Class A for a fortnight into four state spaces, i.e., $m = 4$, then $\Delta e = (550.58 - 348.32)/4 = 50.565$, at which point the state spaces (noted as states 1, 2, 3, 4) are divided as follows:

$$\begin{aligned} &\text{State 1} = [3.48.32, 398.885],\ \text{State 2} = [398.885, 449.45] \\ &\text{State 3} = [449.45, 500.015],\ \text{State 4} = [500.015, 550.58]. \end{aligned} \tag{16}$$

The average energy consumption for all 2 weeks in Class B is divided into four state spaces, i.e., $m = 4$, then $\Delta e = (348.12 - 236.28)/4 = 27.96$, at which point the state spaces (noted as states 1, 2, 3, 4) are divided as follows:

$$\begin{aligned} &\text{State 1} = [236.28, 264.24],\ \text{State 2} = [264.24, 292.20] \\ &\text{State 3} = [292.20, 320.16],\ \text{State 4} = [320.16, 348.12]. \end{aligned} \tag{17}$$

Based on the above division of the state space, statistics on the transfer of average exercise energy expenditure for all individuals in Class A over the adjacent two weeks can be derived, as shown in Table 9.

Table 9: Statistics on the average exercise energy consumption and transfer of all individuals

Number of transfers		**Week 2**				**Amount to**
		State 1	**State 2**	**State 3**	**State 4**	
Week 1	State 1	2	2	0	0	4
	State 2	1	1	0	1	3
	State 3	2	1	0	0	3
	State 4	0	0	2	0	2

Comparable transfer statistics may be produced for the average exercise energy consumption of every person in Class B over the preceding 2 weeks, as shown in Table 10.

Table 10: Statistics on the average exercise energy consumption and transfer of all individuals in Class B during the adjacent 2 weeks

Number of transfers		Week 2				Amount to
		State 1	State 2	State 3	State 4	
Week 1	State 1	2	1	0	0	3
	State 2	2	2	2	0	6
	State 3	1	0	1	1	3
	State 4	0	2	0	0	2

Based on the transfer statistics in Tables 9 and 10, the transfer probability matrices for the average exercise energy expenditure of all individuals in Classes A, B for the two adjacent weeks can be calculated separately as follows:

$$P_A = \begin{bmatrix} 0.25 & 0.75 & 0 & 0 \\ 0 & 0.67 & 0.33 & 0 \\ 0.33 & 0.67 & 0 & 0 \\ 0 & 0 & 0.5 & 0.5 \end{bmatrix}$$
$$P_B = \begin{bmatrix} 0.33 & 0.67 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 \\ 0 & 0.33 & 0 & 0.67 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \tag{18}$$

Based on the formula for transfer progression, the transfer progression for classes A, B can be calculated separately:

$$K_A = 0.75 \times (2-1)^3 + 0.33 \times (3-2)^3 + 0.33 \times (1-3)^3 + 0.67 \times (2-3)^3 + 0.5 \times (3-4)^3 = -2.73$$
$$K_B = 0.67 \times (2-1)^3 + 0.67 \times (4-3)^3 + 0.5 \times (1-2)^3 + 0.33 \times (2-3)^3 = 0.51. \tag{19}$$

Based on the results of the above calculations, it can be seen that Class A's transfer progression was −2.73, indicating that Class A exercise regressed in week 2 compared to week 1, while Class B's transfer progression was 0.51, indicating that Class B exercise improved in week 2 compared to week 1. It can be judged that during the two consecutive weeks, Class B had a better exercise effect than Class A.

6 Conclusion

Youth sports physical health data should receive repeated attention, and to this end, this article has designed a student physical health management platform based on a cloud-based management platform, whose main role is to provide youth with easy access to sports life. We also collected sensor data for detecting gait patterns (with or without leg contact) and filtered it through an AHF to differentiate between the two patterns. To validate the proposed health evaluation model for sports groups, the model was compared with the traditional mean comparison method to derive the validity of the data analysis for the proposed model.

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