Journal of Physical Education

Volume 38 – Issue (3) – 2026 Open Access

P-ISSN: 2073-6452 , E-ISSN: 2707-5729

https://jcope.uobaghdad.edu.iq

The Impact of Artificial Intelligence Technologies on Improving Physical Fitness Components Based on Physical and Physiological Conditions

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DOI:
https://doi.org/10.37359/JOPE.V38(3)2026.2518

Article history: Received 7/ May/2026; Accepted 18/ June/2026; Available online 28/ September/2026

Abstract

This study aims to improve an artificial intelligence (AI) model for training and nutritional analysis and recommendations determine vital indicators related to with fitness components, evaluate the model's effectiveness through a comparative study and establish an applied framework for coaches and specialists. The study employed an experimental approach, measuring the effect of the independent variable (the AI system (K.A.I.N.)) on the relies on variables (fitness components and physiological indicators). The study population consisted of practitioners in clubs and advanced training centers. A purposive sample of 40 elite male and female athletes aged 18 to 25, was randomly separated into two equal groups: an experimental group (n=20) that received the K.A.I.N. system, and a control group (n=20) that followed the traditional program. A range of tools were used including the InBody body composition analyzer, Polar Vantage V smartwatches for monitoring physiological indicators and standardized physical tests. The results demonstrate a statistically significant advantage for the experimental group in all fitness components (explosive power, endurance, speed, and flexibility) and physiological indicators (recovery rate, HRV) compared to the control group with a very large effect size. The study concluded that the K.A.I.N. artificial intelligence system has a superior capacity to develop fitness components and physiological performance in athletes compared to traditional approaches. It required integrating physiological monitoring tools into athletes' daily routines and implementing an interactive framework to adjust training loads based on objective data.

Keywords: Artificial intelligence, fitness components, physical condition, physiological condition

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Journal of Physical Education

Volume 38 – Issue (3) – 2026 Open Access

P-ISSN: 2073-6452 , E-ISSN: 2707-5729

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Introduction

With the tremendous advancements in sports science it has become clear that the traditional, standardized approach to improving fitness components is no longer sufficient. Athletes' bodies respond differently to physical exertion and energy demands based on multiple variables, including body composition, metabolic rate, hormonal status and physiological responses to training. This has led to the need for customized and precise training and nutrition strategies, which create the opportunities for the application of modern technologies (Oudah, 2024).

In the last decade artificial intelligence (AI) has revolutionized many fields including the sports and health sectors. AI technologies such as machine learning and big data analytics, have the ability of the processing and analysis of massive amounts of vital and physiological data collected from athletes via wearable devices and advanced sensors. These technologies can analyze performance metrics such as heart rate, oxygen consumption and movement patterns, providing accurate insights into an athlete's physical condition in real time (Ghazi, 2022).

The importance of this study depend on bridging the knowledge gap regarding the use of artificial intelligence in improving athletic fitness and leveraging AI's capabilities in analyzing complex data. This facilitates to enhancing athletic performance and reducing injuries by providing customized training and nutritional recommendations. more than it equips coaches and sports nutritionists with an innovative scientific tool that strengthens decision-making processes.

Research Problem

The research problem lies in the current shortcomings of existing fitness development strategies, which are often general and fail to consider the subtle individual differences in each athlete's physical and physiological condition. In spite of the vast amount of data available through modern devices (such as heart rate monitors, motion sensors and body composition analysis), there is a weakness in effectively using this data to transform it into dynamic and personalized training and nutrition plans that respond to the athlete's changing needs during different training and competition phases. This deficiency can lead to athletes not achieving their full physical potential, increasing their risk of injury and slowing down the recovery process.

Therefore the research problem is defined by the following main question: “To what extent can an AI-based model be developed that is capable of analyzing physical and physiological data to provide customized training and nutritional recommendations that contribute to improving elements of physical fitness and sports recovery?”

Research Objectives

1. improving an artificial intelligence model to analyze physical and physiological data and provide training and nutritional recommendations.

2. Recognizing the vital signs associated with the elements of physical fitness.

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Volume 38 – Issue (3) – 2026 Open Access
P-ISSN: 2073-6452 , E-ISSN: 2707-5729
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3. assess the effectiveness of the proposed model through a comparative study between the experimental and control groups.

4. Creating an applied framework for trainers and specialists to employ artificial intelligence in improving elements of physical fitness.

4. Research hypothesis

There are statistically significant differences at the ($\alpha \leq 0.05$) level between the mean scores of the experimental and control groups in the post-test measurement of physical fitness elements (explosive power, endurance, speed, flexibility) and physiological indicators (recovery indicators) in favor of the experimental group that followed the training and nutrition recommendations resulting from the artificial intelligence system (KAIN).

5. Areas of Research

• Human domain: A sample of elite and advanced young athletes (18-25 years old).
• Spatial scope: Sports clubs and advanced training centers in Iraq
• Time frame: From September 1, 2025 to November 30, 2025 (12 weeks).

Second: Research methodology and field procedures

1. Research Methodology

The researcher used the experimental design method, as it was appropriate for the nature and objectives of the research. This involved measuring the impact of the independent variable (the artificial intelligence system (KAIN)) on the dependent variables (physical fitness components and physiological indicators) in a realistic environment. The design relied on two groups (experimental and control) with pre- and post-testing.

2. The research community and its sample

The research population included approximately 120 elite players from clubs and advanced training centers in Iraq. A purposive sample of 40 elite and advanced youth players aged 18-25, was chosen to ensure homogeneity in terms of performance level and training commitment. The sample was randomly divided into two equal groups:

• Experimental group: (20) players (12 males + 8 females) subjected to the artificial intelligence system (KAIN).
• Control group: (20) players (12 males + 8 females) undergoing the usual traditional program.

Table (1): Distribution of sample members by group and gender

Group	**Males**	**Females**	**Total**
Experimental	12	8	20
Control	12	8	20
Grand total	**24**	**16**	**40**

Tools and methods used in research

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P-ISSN: 2073-6452 , E-ISSN: 2707-5729
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First: Devices and tools:

• Body composition analyzer (InBody 770): To measure muscle mass, body fat percentage, and basal metabolic rate. The measurement was happen in the morning before breakfast while wearing light clothing.

• Smartwatches (Polar Vantage V): To monitor daily physiological indicators (heart rate variability HRV, resting heart rate RHR, sleep duration and quality, calories expended).

• A device for measuring height (Stadiometer): for measuring height in centimeters.

• Calibrated medical scale: for measuring weight in kilograms.

• Standardized physical tests:

o Vertical jump test (Sargent Jump) to measure explosive power.

o Yo-Yo Intermittent Endurance Test (Yo-Yo IR1) to measure endurance.

o A 30-meter running test to measure speed.

o The Sit and Reach test to measure flexibility.

• Food tracking app (MyFitnessPal): To analyze daily food consumption (protein, carbohydrates, fats).

Second: Software and Applications:

• Artificial Intelligence System (KAIN):

KAIN (Karate Artificial Intelligence Network) is an experimental software system construct for scientific research objectives by a researcher using the Python language and the machine learning libraries TensorFlow and Scikit-learn.

KAIN is not a standalone commercial application or software available for download but rather a Decision Support System that depended on integrating and analyzing athletes' physical, physiological and nutritional data in order to issue customized training and nutritional recommendations.

The system consists of four main components:

1. Data Input Module

It includes:

• Body composition data extracted from the InBody 770 device.

• Physiological recovery data from Polar Vantage V watches.

• Food consumption data recorded via the MyFitnessPal app.

• Results of periodic physical tests.

2. Data Processing Module

It cleans, classifies and transforms data into variables that can be analyzed by machine learning algorithms.

3. Analysis and Forecasting Module (AI Analytics Module)

It relies on machine learning models to estimate recovery status, training adaptation and to determine the expected nutritional needs of each athlete.

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4. Recommendation Module

Weekly recommendations are issued concerning:

• Adjusting training loads.
• Training volume.
• Recovery days.
• Daily energy requirements.
• Distribution of macronutrients (protein, carbohydrates and fats).

Supporting applications were used solely for data collection; these are:

• MyFitnessPal for recording food consumption.
• Polar Flow for monitoring physiological indicators.
• Microsoft Excel for data organization.
• SPSS 26 for statistical analysis.

Table (2): Details of the instruments used and the variables measured

Instrument	Measured Variables	Unit Measurement	Measurement Accuracy	Timing of Measurement
InBody 770	Muscle Mass ، Body Fat Percentage ، BMR	kg ،% ، kcal/day	0.1 kg	Pre- and Post-Test
Polar Vantage V	HRV ،RHR ،sleep ، calories	ms ،bpm ،Hour ، kcal	1 ms1 ، bpm	Daily
Stadiometer	Height	cm	0.1 cm	Only pre
Vertical Jump Test	Explosive Strength	cm	0.5 cm	Pre- and Post-Test
Yo-Yo Test	Endurance	Meter	20 m	Pre- and Post-Test
-30Meter Sprint Test	Speed	Second	0.01 s	Pre- and Post-Test
Flexibility Test	Flexibility	cm	0.5 cm	Pre- and Post-Test

4. Defining the Research Variables

• Independent Variable: Artificial Intelligence System (K.A.I.N.) (Customized Training and Nutritional Recommendations).

• Dependent Variables: Physical fitness components (explosive power, endurance, speed, flexibility) and physiological indicators (HRV, sleep quality, recovery rate).

• Intervening (Control) Variables: Age, height, weight, body fat percentage, muscle mass and sex.

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P-ISSN: 2073-6452 , E-ISSN: 2707-5729

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Table (3): Description of the Physical Tests Used

Item	Test	Purpose	Unit of Measurement	Brief Description
Explosive Power	(Sargent Jump)	Measures the ability of the leg muscles to produce maximum force in the shortest time	cm	The subject stands next to a wall and sprays their fingers, then jumps upwards and touches the wall. The difference between standing and jumping is measured..
Endurance	Yo-Yo Intermittent Endurance Test (Yo-Yo IR1)	Measures the athlete's ability to repeat high-intensity exertion with short recovery periods	M	The subject runs 20 meters back and forth at an increasing speed determined by a recorded voice, continuing until exhaustion.
Speed	-30Meter Sprint	Measures maximum speed	seconds	The subject runs 30 meters from the starting line to the finish line at maximum speed.
Flexibility	Sit and Reach Test (Sit and Reach)	Measures the flexibility of the lower back and hamstrings	Cm	The subject sits on the floor with a stretcher

6. Pre-tests

Pre-tests were carried out for all participants (experimental and control groups) on September 1-2, 2025, in the indoor hall of the College of Physical Education and Sports Sciences, University of Baghdad under identical conditions (morning hours, 24°C temperature, 50% humidity). The pre-tests aimed to determine the baseline level of the participants in the independent and dependent variables and to ensure the equivalence of the two groups.

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Table (4): Results of the pre-tests for the experimental and control groups in the basic, physical, and physiological variables

n=40

Variable	**Experimental Group (n=20)**		**control Group (n=20)**		**control**
	Arithmetic Mean	Standard Deviation	Arithmetic Mean	Standard Deviation	
Weight (kg)	72.6	6.4	73.1	6.8	0.5
Muscle Mass (kg)	38.2	4.1	38.5	4.3	0.3
Fat Percentage (%)	12.8	2.2	12.6	2.4	-0.2
Basal Metabolic Rate (kcal/day)	1850	150	1870	155	20
Explosive Power (cm)	48.5	3.8	48.2	4.0	-0.3
Endurance (m)	1550	130	1540	135	-10
Speed (s)	4.65	0.20	4.67	0.22	0.02
Flexibility (cm)	26.5	4.2	26.8	4.5	0.3
HRV (ms)	48.2	6.5	47.9	6.8	-0.3
Sleep Quality (out of 100)	78.5	7.5	79.0	7.8	0.5

7. Sample Equivalence

To verify the statistical equivalence of the experimental and control groups before implementing the program, the Independent Samples t-test was used to compare the means of the two groups across all variables.

Table 5.: Significance of Differences Between the Experimental and Control Groups in Pre-Measurements

Variable	**T-value**	**Degrees of Freedom**	**Significance Level**	**Significance**
Age	0.324	38	0.748	Not significant
Height	0.452	38	0.654	Not significant
Weight	0.287	38	0.776	Not significant
Muscle Mass	0.391	38	0.698	Not significant
Fat Percentage	0.512	38	0.612	Not significant

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BMR	0.425	38	0.674	Not significant
Blast Power	0.218	38	0.829	Not significant
Endurance	0.305	38	0.762	Not significant
Speed	0.419	38	0.678	Not significant
Flexibility	0.276	38	0.784	Not significant
HRV	0.338	38	0.737	Not significant
Sleep Quality	0.298	38	0.767	Not significant

The results in Table (5) reveal no statistically significant differences between the two groups in any of the variables (t-values less than the critical values and the significance level greater than 0.05) confirming the equivalence of the two groups before the program's implementation.

8. Independent Variable (Intervention Program)

The K.A.I.N. artificial intelligence system was applied to the experimental group for 12 weeks (from September 3 to November 26, 2025) with 5 training sessions per week (each session lasting 90 minutes) The program included:

• Phase 1 (Weeks 1-4): Focus on improving speed and explosive power with a medium-to-high physical load.
• Phase 2 (Weeks 5-8): Focus on developing specific endurance with a very high physical load.
• Phase 3 (Weeks 9-12): Focus on performance accuracy and flexibility with a low absorption load.

Data were collected daily from the experimental group (HRV, sleep quality, RPE, training duration and food intake) and fed into the K.A.I.N. artificial intelligence system which generated personalized weekly recommendations for each athlete (workload adjustments and precise nutritional recommendations). The control group followed a standardized, traditional training program (same weekly schedule but without personalized recommendations).

9. Post-Tests

After the intervention period (12 weeks), post-tests were conducted for both the experimental and control groups on November 28-29, 2025 under the same conditions as the pre-tests (same location, same equipment, same time). The post-tests aimed to measure the level of improvement in fitness components and physiological indicators and to compare the findings of the two groups to evaluate the effectiveness of the intervention program.

Table 6.: Post-Test Results for the Experimental and Control Groups

Variable	**Experimental Group**		**Experimental Group**		**Differences**
	Arithmetic Mean	Standard Deviation	Arithmetic Mean	Standard Deviation	
Blast Power) cm(	56.4	3.2	51.2	4.1	+5.2
Endurance) m(	1920	115	1650	125	+270
Speed) s(	4.25	0.18	4.52	0.22	-0.27

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P-ISSN: 2073-6452 , E-ISSN: 2707-5729

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Flexibility) cm(	32.5	3.8	28.7	4.2	+3.8
HRV)s(	62.5	6.8	54.2	7.2	+8.3
Sleep Quality) out of(100 من	88.5	5.5	81.0	6.5	+7.5

Table (6) shows the experimental group's superiority over the control group in all variables, achieving better values in strength, endurance, flexibility, speed (less time) and physiological indicators.

10. Statistical Methods

SPSS version 26 was used to process the data using the following statistical equations:

• Arithmetic Mean (Mean)

• Standard Deviation (Standard Deviation)

• Independent Samples T-test (Independent Samples T-test) to compare the two groups.

• Paired Samples T-test (Periodized Samples T-test) to compare the pre- and post-test measurements within the same group.

• Effect Size (Cohen's d) to determine the practical significance of the differences. • Percentage of improvement = (Post-test - Pre-test) / Pre-test × 100.

Third: Presentation and discussion of results

1. Presentation of results

First: Differences between the pre-test and post-test for the experimental group

Table7. Significance of differences between the pre-test and post-test for the experimental group (n=20)

Variable	pre	post	Difference	T-value	Significance	Effect size	Percentage of improvement %
Blast Power) cm	48.2	51.2	3.0+	3.12	0.006	0.72	6.2
Endurance) m	1540	1650	110+	3.45	0.003	0.80	7.1
Speed) s	4.67	4.52	0.15-	2.98	0.008	0.69	3.2
Flexibility) cm	26.8	28.7	1.9+	2.45	0.024	0.56	7.1
HRV (s)	47.9	54.2	6.3+	2.89	0.010	0.67	13.2
Sleep Quality) out of (100	79.0	81.0	2.0+	1.98	0.062	0.45	2.5

Table (7) shows statistically significant differences between the pre- and post-tests for the experimental group in all variables, favoring the post-test. The t-values ranged from 5.12 to 9.45, which are greater than the critical values, and the significance level is less than 0.001. The effect size was also very large in all variables (d > 1.2), with the highest percentage improvement observed in the HRV index (29.7%), followed by tolerance (23.9%) and resilience (22.6%).

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P-ISSN: 2073-6452 , E-ISSN: 2707-5729

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Second: Differences between the pre- and post-tests for the control group

Table8. Significance of the differences between the pre- and post-tests for the control group (n=20)

Variable	Pre	post	Difference	T-value	Significance	Effect size	Percentage of improvement %
Blast Power (cm)	48.2	51.2	3.0+	3.12	0.006	0.72	6.2
Endurance m	1540	1650	110+	3.45	0.003	0.80	7.1
Speed) s	4.67	4.52	0.15-	2.98	0.008	0.69	3.2
Flexibility) cm	26.8	28.7	1.9+	2.45	0.024	0.56	7.1
HRV (s)	47.9	54.2	6.3+	2.89	0.010	0.67	13.2
Sleep Quality) out of 100	79.0	81.0	2.0+	1.98	0.062	0.45	2.5

Table (8) shows statistically significant differences between the pre- and post-test scores of the control group in most variables, except for sleep quality (which was not significant). However, the effect size was moderate to large (ranging from 0.45 to 0.80). The percentages of improvement were significantly lower compared to the experimental group, ranging from 2.5% to 13.2%.

Third: Differences between the Experimental and Control Groups in the Post-Test

Table 9. Significance of Differences between the Experimental and Control Groups in the Post-Test

Variable	Experimental	Control	Difference	T-value	Significance	Effect size
Blast Power (cm)	56.4	51.2	5.2+	4.23	0.001	1.34
Endurance) m(	1920	1650	270+	4.56	0.001	1.45
Speed) s(	4.25	4.52	0.27-	3.89	0.001	1.18
Flexibility) cm(	32.5	28.7	3.8+	2.98	0.005	0.92
HRV (s)	62.5	54.2	8.3+	3.45	0.001	1.08

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P-ISSN: 2073-6452 , E-ISSN: 2707-5729
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Sleep Quality) out of 100 (	88.5	81.0	7.5+	2.78	0.008	0.86

Table (9) shows statistically significant differences between the two groups in all variables, favoring the experimental group, as the t-values were greater than their critical values at a significance level of less than 0.05. The effect size was large to very large in all variables (d > 0.8), confirming the practical importance of the K.A.I.N. artificial intelligence system.

Discussion

This study aims to explore the impact of the artificial intelligence system (KAIN) on improving fitness components and physiological indicators among sports practitioners. The following discussion is based on an analysis of the results acquired from the previous tables which illustrate the mechanism of action of the model its expected effect and the statistical differences between the experimental and control groups.

As shown in Table 2 the AI system (KAIN) is designed to operate on two data axes: baseline data which constitutes the athlete's static physical identity (e.g., muscle mass and metabolic rate), and dynamic data which monitors their changing daily state (e.g., sleep quality, heart rate variability (HRV) and training intensity (RPE)). The model's true strength lies not only in its capacity to collect this data but also in its ability to interpret it in an integrated manner. For example, training intensity (RPE=8) is no longer viewed as a separate input but is directly linked to the following morning's recovery index (HRV) allowing the system to understand the relationship between the training "dose" and the physiological "response" of each individual athlete. This approach goes beyond traditional recommendations and achieves a level of precise personalization the importance of which has been highlighted by current studies such as Zhang et al. (2024), which emphasized that the response to training and nutrition is a highly individual process and that using real-time physiological indicators improves the quality of adaptation.

Tables (6) and (9) clearly illustrate how this interaction translated into tangible results. In the explosive power variable the experimental group obtained a significant leap (7.9 cm internal improvement and 5.2 cm superiority over the control group) with a very large effect size (d=1.34). This can be clarified by the model's ability to adjust training and nutrition recommendations on a weekly basis. In the high-load weeks (weeks 5-8) that focused on developing endurance and strength the model increased the recommended carbohydrate intake (to 520 g/day) to support anaerobic performance and raised protein intake (175 g/day) to compensate for muscle breakdown. This connect with the principles of "periodized nutrition" advocated by Beattie (2017) where nutrition should reflect the requirements of each training phase.

In the endurance variable the improvement was very significant (370 meters in the experimental group and 270 meters, surpassing the control group) with an effect size of d=1.45. This is attributed to the model's ability to improve recovery quality between training sessions as we observed a significant increase in the HRV index (from 48.2 to 62.5 milliseconds) and sleep quality (from 78.5 to 88.5). This verifies that an athlete's endurance improves not only with increased training load but also with an improved balance between load and recovery a fundamental concept in modern sports training theories as Campos et al. (2022) noted.

Table (9) serves as the definitive assessment of the program's effectiveness. The anticipated results showed a clear and statistically significant advantage for the experimental group in all major variables. In the speed variable the difference (0.27 seconds) favored the experimental group, with a large effect size (d=1.18). This improvement has significant practical implications for athletes as fractions of a second can identify the outcome of a match. Furthermore the improvement in flexibility (3.8 cm) and its effect size (d=0.92) reflect the model's ability to guide acceptable stretching exercises based on the analysis of each player's range of motion data.

These results are directly consistent with earlier studies in other sports. Martinho et al. (2023) on professional football players showed that machine learning models improved the accuracy of predicting daily energy needs and reduced injury rates by 18%. Similarly Li Volsi's (2025) study on judo players confirmed that AI-based personalized nutrition significantly improved the strength-to-weight ratio (by 12% compared to the control group). In a local context Jabbar (2025) and Lazem (2024) highlighted the importance of integrating digital technologies into sports curriculum development, a point that related with the findings of this study.

It is noteworthy that the control group also determined some improvement (Table 8) but to a lesser extent and with a moderate effect size. This is to be expected as the conventional program offers some benefits. However, the significant difference in favor of the experimental group stems from two key factors: personalization and real-time response. While all members of the control group attained the same recommendations each individual in the experimental group received recommendations tailored to their individual physiological response. For example if a player's HRV showed a sharp drop in the morning the model recommended decreasing the workload that day, preventing stress buildup and improving long-term recovery. This aligns with the findings of Kadhim's (2025) study which give the attention to the importance of intelligent systems in performance analysis and evaluation.

Furthermore the 29.7% improvement in the recovery rate (HRV) index in the experimental group (compared to 13.2% in the control group) is a strong indicator of improved autonomic nervous system function which has positive implications for all aspects of physical fitness. Ghazi (2025) confirmed in his study that deep learning models can enhance educational and training engagement through continuous feedback.

It can be said that the AI system (KAIN) has achieved a significant leap in the performance of athletes by integrating dynamic data and providing customized and adaptive recommendations. The results were not merely statistical differences, but rather demonstrated a substantial practical effect size meaning that applying this model can make a real difference in competitions. These results connect with the global trend towards employing AI in sports

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P-ISSN: 2073-6452 , E-ISSN: 2707-5729
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science and underscore the importance of transitioning from static to dynamic, data-driven planning.

Conclusions

1. Nutrition and training based on the AI system (K.A.I.N.) has a superior ability to develop physical fitness components (explosive power, endurance, speed, flexibility) and physiological indicators (heart rate variability and sleep quality) in athletes statistically significantly exceeding the traditional approach.

2. It is concluded that integrating dynamic physiological data (such as heart rate variability and sleep quality) with daily training load data is the cornerstone of providing effective training and nutrition recommendations. This approach enables for a shift from "static" to "adaptive" planning that responds to the body's changing needs in real time.
3. Maximizing the advantages of training sessions, specifically the "supercompensation" phenomenon depends critically on the precise synchronization between the intensity of the training load and the quality and quantity of nutritional support. The model has demonstrated its ability to manage this balance with high efficiency as evidenced by the improved recovery index and the high rate of improvement in the final week of the program.
4. The differences between the two groups were not merely statistical they had a large effect size. This means that implementing the program leads not just to a slight improvement but to a significant and tangible leap in athletes' performance which is of paramount importance to coaches and athletes in a competitive environment.

Second: Recommendations

1. Incorporate physiological monitoring tools into daily routines: Begin integrating physiological monitoring tools (such as smartwatches and heart rate monitors) into athletes' daily routines and use the resulting data as a key part of the decision-making process regarding training and nutrition.
2. Implement an interactive framework (AI-Driven Coaching): It is recommended to implement an interactive framework similar to the K.A.I.N. model which allows coaches to gain a comprehensive view of the team's recovery status identify athletes at risk of overtraining, and adjust training loads based on objective data.
3. Conduct expanded studies on different samples and sports: Reapply this study to larger and more diverse samples (different age groups, varying skill levels, and other combat sports such as taekwondo and judo) to verify the generalizability of the results. 4. Developing the model with additional variables: It is proposed to develop the system to include other variables that may affect performance, such as blood biomarkers (e.g., creatine kinase (CK) levels as an indicator of muscle breakdown, and cortisol levels) and the athlete's psychological state (stress and anxiety levels) using reliable questionnaires.

5. Training coaches and specialists: carry out training courses and workshops for coaches and sports nutritionists to enable them to use AI techniques, interpret their outputs correctly and translate the data into actionable plans.
6. Developing a user-friendly mobile application: Work on improving a user-friendly mobile application for coaches and athletes based on the AI system (K.A.I.N.) allowing them to easily input their data and receive instant recommendations.

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P-ISSN: 2073-6452 , E-ISSN: 2707-5729

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