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Precision Exercise Programming in Optimizing Cardiometabolic Health and Physical Performance through Artificial Intelligence Assisted Training

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A B S T R A C T

The development of artificial intelligence allows for the development of more precise exercise programs based on individual physiological responses, but its effectiveness on cardiometabolic health and physical performance still requires empirical testing. This study aims to analyze the effect of artificial intelligence-assisted training on cardiometabolic indicators and physical performance. The study used a 12-week randomized controlled trial of 120 participants allocated to an AI-based exercise group and conventional exercises. Data were collected through measurements of VO_2max, blood pressure, resting heart rate, body composition, blood glucose, as well as strength and endurance tests, and then analyzed using the mixed-ANOVA model. The results showed the AI-based group experienced significant improvements in VO_2max, strength, and endurance as well as improvements in cardiometabolic indicators. These findings confirm the potential of AI in optimizing exercise personalization and the effectiveness of exercise interventions.

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INTRODUCTION

Physical activity and exercise are important components in preventing non-communicable diseases and increasing functional capacity. However, global physical activity levels are still a public health issue. An analysis of 507 population-based surveys from 197 countries and regions shows that about 31.3% or 1.8 billion adults in the world did not meet physical activity recommendations in 2022, an increase from 23.4% in 2000 (Strain et al., 2024). These conditions contribute to an increased risk of cardiometabolic disorders, including hypertension, obesity, insulin resistance, and cardiovascular disease. This problem is also relevant for Indonesia as a country that faces an increasing burden of non-communicable diseases, so an exercise strategy is needed that not only increases sports participation, but is also able to produce optimal physiological adaptation.

The effectiveness of exercise is influenced by the intensity, volume, frequency, physiological condition, and adaptive response of each individual. Ramos et al. (2021) showed that differences in exercise intensity resulted in variations in responses to the fitness-fatness index in individuals with metabolic syndrome, with the proportion of clinical responses tending to be higher in high-intensity interval exercise than in moderate-intensity continuous exercise. The findings reinforce the concept of precision exercise, which is the preparation of exercise doses based on individual characteristics and responses, rather than simply using the same program for all participants. Kirton et al. (2022) also found that an individualized aerobic exercise approach based on ventilation thresholds provided a more favorable pattern of fitness improvement than an exercise approach based solely on a reserve heart rate percentage.

The development of artificial intelligence (AI), machine learning, and wearable devices opens up opportunities to develop more adaptive precision exercise programming. Data such as heart rate, training load, fatigue level, rating of perceived exertion, recovery, and previous performance can be analyzed to dynamically adjust the intensity and volume of exercise. Guan et al. (2022) showed that individual exercise combined with remote management was able to improve body weight, body fat, blood pressure, glucose metabolism, and insulin resistance in overweight or obese individuals. Meanwhile, Li and He (2025) show the potential of AI algorithms in utilizing sensor data to generate individualized training plans that support athlete performance improvement.

However, there is an important research gap. Kirton et al.'s (2022) research focuses on individualization based on physiological parameters without using AI as an exercise adaptation system, while Guan et al. (2022) use remote exercise management but have not yet integrated AI algorithms to dynamically adjust programs. The Li and He (2025) study emphasizes more on prediction and performance optimization in certain sports, so the implications for cardiometabolic indicators are inadequate. More critically, Dergaa et al. (2024) found that AI such as GPT-4 is capable of generating general exercise recommendations, but still has limitations in individual precision, exercise progression, and integrated physiological feedback on an ongoing basis. Thus, there is still limited controlled experimental research that directly compares AI-assisted personalized training with conventional exercise and assesses cardiometabolic outcomes and physical performance simultaneously.

Based on these gaps, this study aims to analyze the effect of artificial intelligence-assisted precision exercise programming on cardiometabolic health and physical performance compared to conventional exercise programs. Specifically, the study was directed to evaluate changes in VO_2max, blood pressure, resting heart rate, body composition, blood glucose, muscle strength, and endurance after a 12-week exercise intervention. This approach is expected to provide empirical evidence regarding AI's ability to personalize exercise doses based on individual physiological responses and result in more optimal exercise adaptations.

Theoretically, this study is expected to expand the development of the concept of precision exercise medicine by integrating the principles of individualization of exercise and AI-based decision-making in explaining cardiometabolic response variations and performance. Practically, the results of the research can be the basis for the development of a digital exercise system that is able to help coaches, sports practitioners, and health professionals in determining the intensity, volume, and progression of exercise in a more objective and adaptive manner. The implementation of AI in this context is not directed to replace professional roles, but rather as a data-driven decision-making support instrument to improve the effectiveness, safety, and personalization of sports interventions.

LITERATURE REVIEW

Precision Exercise Programming and Individual Variability

Precision exercise programming evolved from the understanding that the physiological response to the same exercise dose is not always uniform between individuals. These variations are influenced by age, gender, initial fitness level, genetics, sleep patterns, nutrition, drug use, and exercise intensity and volume. Lehtonen et al. (2022) assert that general guidelines-based approaches are often not able to accommodate the heterogeneity of cardiorespiratory fitness responses, so the determination of intensity and volume needs to be adjusted to individual characteristics. This is reinforced by Noone et al. (2024), who explain that variation in exercise responses is the result of an interaction of intrinsic and extrinsic factors. Thus, precision exercise provides a theoretical basis for a program that continuously adjusts the exercise dose based on the participants' actual responses.

Individualized Exercise and Cardiometabolic Health

Personalization of exercise becomes important in the management of cardiometabolic risk factors because changes in blood pressure, body composition, glucose metabolism, and aerobic capacity can differ even if individuals receive similar exercise interventions. Kim et al. (2024), through a scoping review, found that individual exercise has the potential to result in improvements in various components of metabolic syndrome, although its effectiveness depends on the accuracy of adjustment of frequency, intensity, duration, and type of exercise. The approach is relevant to the use of VO_2max, blood pressure, resting heart rate, body composition, and blood glucose as indicators of response to interventions. Therefore, optimizing cardiometabolic health requires a system that not only provides an initial program, but is also capable of adjusting the exercise load based on the physiological development of the participant.

Wearable Technology and Physiological Monitoring

The implementation of precision exercise is increasingly possible through the development of wearable technology that can record activity and physiological responses continuously. Seçkin et al. (2023) show that wearable sensors have been used for real-time monitoring of heart rate, motion, training load, performance, and evaluation of athletes' recovery. This information provides an objective basis for assessing whether individuals are able to maintain, improve, or even need to decrease the exercise dose. However, wearable data does not automatically produce the right training decisions. The quality of the sensor, the validity of the measurements, the interpretation of the data, and the integration of various physiological parameters still determine the effectiveness of its use in the personalization of the program.

Artificial Intelligence-Assisted Training and Adaptive Exercise

The integration of artificial intelligence with wearable data allows the personalization process to evolve from just monitoring to an adaptive decision-making system. Chen et al. (2021) developed an AI-based exercise prescription recommendation system that demonstrates the ability of computational technology to process individual characteristics into more specific exercise recommendations. Further developments show that machine learning can process sensor data and identify patterns that are difficult to determine through manual observation. Vec et al. (2024), through a review of 72 studies, found rapid development in the use of machine learning and deep learning in sports, particularly in sensor data processing and providing real-time feedback. The findings support the concept of AI-assisted training as a system that can use data such as heart rate, exercise intensity, previous performance, fatigue, and recovery to dynamically adjust the program.

Artificial Intelligence and Physical Performance

In the context of physical performance, AI can be used to analyze training load, movement patterns, fatigue levels, and performance changes so that trainers can optimize stimuli without increasing the risk of undertraining or overtraining. Munoz-Macho et al. (2024) show that the utilization of AI in elite sports has evolved in performance analysis, health monitoring, injury prevention, and decision-making support. Meanwhile, Jubair and Mehenaz (2025) found that the integration of machine learning with smartwatches has the potential to support personalized exercise recommendations as well as continuous physiological monitoring. Therefore, the AI-assisted training mechanism can theoretically increase strength and endurance through progressive adjustments of intensity, volume, recovery, and training load based on individual responses.

Conceptual Synthesis and Research Proposition

Based on the literature, precision exercise programming can be understood as the process of integrating individual characteristics, physiological responses, exercise loads, and performance data to produce adaptive exercise doses. Wearables serve as a data source, while AI plays a role in recognizing patterns and generating program adjustment recommendations. Although various studies have shown the potential of individualization, wearables, and AI separately, experimental evidence directly evaluating whether AI-assisted training systems result in greater changes in cardiometabolic health and physical performance than conventional exercise is still limited. This condition provided the basis for a 12-week study that compared AI-assisted groups and conventional exercise through changes in VO_2max, blood pressure, resting heart rate, body composition, blood glucose, strength, and endurance. Thus, the conceptual framework of the study positions the use of AI in exercise personalization as a factor that is expected to improve the effectiveness of cardiometabolic adaptation and physical performance.

Research Hypotheses

Based on the theoretical framework and findings of previous research, the use of artificial intelligence-assisted training is estimated to be able to produce more optimal exercise responses through adjustment of intensity, volume, and exercise progression based on individual physiological conditions. Thus, this study proposes the main hypothesis that participants who follow AI-assisted precision exercise programming will show greater improvements in cardiometabolic health and physical performance than participants who follow a conventional exercise program.

Specifically, the research hypothesis is formulated as follows:

H1: AI-assisted training resulted in a greater increase in VO_2max than conventional training after 12 weeks of intervention.

H2: AI-assisted training resulted in greater reductions in systolic and diastolic blood pressure than conventional training after 12 weeks of intervention.

H3: AI-assisted training resulted in a greater reduction in resting heart rate compared to conventional training after 12 weeks of intervention.

H4: AI-assisted training results in greater improvements in body composition, which is demonstrated by weight loss, BMI, waist circumference, and body fat percentage as well as an increase in muscle mass compared to conventional exercise.

H5: AI-assisted training resulted in greater improvements in metabolic indicators, especially fasting blood glucose reductions, compared to conventional training after 12 weeks of intervention.

H6: AI-assisted training resulted in a greater increase in muscle strength than conventional training after 12 weeks of intervention.

H7: AI-assisted training resulted in a greater increase in physical endurance than conventional training after 12 weeks of intervention.

Statistically, the main hypothesis of the study was tested through the effects of group × time interactions (group × time interaction). The zero hypothesis states that there was no difference in changes in cardiometabolic outcomes or physical performance between the AI-assisted training group and the conventional exercise group from baseline to the end of the intervention. In contrast, an alternative hypothesis states that the change in outcomes differs significantly, with a greater direction of improvement in the AI-assisted training group.

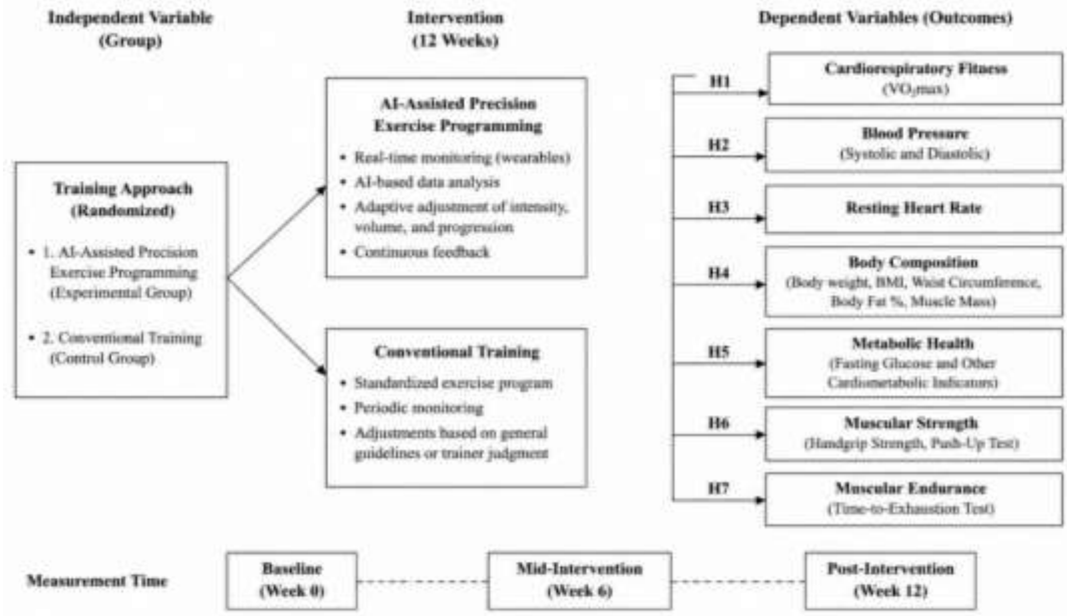

Figure 1. Conceptual Framework

METHODOLOGY

Types of Research

This study used an experimental quantitative approach with a parallel-group randomized controlled trial (RCT) design for 12 weeks. This design was chosen to directly test the effectiveness of artificial intelligence-assisted precision exercise programming compared to conventional exercise on changes in cardiometabolic health and physical performance. Participants were randomly allocated into two groups, namely the AI-assisted training group and the conventional training group. RCTs allow for control of early differences between groups as well as support the assessment of causal relationships between exercise intervention types and changes in physiological outcomes. A similar approach has been used in sports intervention research to evaluate changes in aerobic capacity, body composition, heart rate, and physical performance after a structured exercise program (Govindasamy et al., 2024; Edelmann et al., 2025).

Population and Sample

The study target population was adult individuals who met the requirement to follow a 12-week structured physical exercise program. A total of 120 participants were recruited using the non-probability purposive sampling technique, which is the selection of participants based on suitability for the needs of the intervention and the ability to follow the entire research series. After the recruitment process, participants were randomly allocated with a 1:1 ratio into an AI-assisted training group of 60 participants and a conventional training group of 60 participants. The separation between the recruitment process and randomization is important because sample selection techniques determine who enters the study, whereas randomization determines the allocation of interventions. The use of balanced allocation in sports RCTs is also commonly applied to improve intergroup comparisons (Edelmann et al., 2025).

Research Instruments

The research data was obtained through objective measurements of VO_2max, systolic and diastolic blood pressure, resting heart rate, body composition, blood glucose, muscle strength, and physical endurance, in accordance with the outcomes that have been established in the abstract and the research hypothesis. VO_2max is used to describe cardiorespiratory fitness; resting blood pressure and heart rate are used as indicators of cardiovascular response; body composition is used to describe changes in body status; while blood glucose is used as a metabolic indicator. Strength and endurance are assessed through standardized physical performance tests. The combination of physiological and performance measurements has been used in sports RCTs to evaluate adaptation to exercise programs (Govindasamy et al., 2024).

Measurements were taken using the same calibrated device and procedure for all participants and at each measurement time. Blood pressure was measured after participants were in a resting state using an automated tool and repeated measurement values were used to improve the consistency of results; This approach is in line with the standardization procedure for blood pressure measurement in contemporary clinical research (BPROAD Study Group, 2023). Since the study did not use questionnaire-based psychological constructs, construct validity testing such as factor analysis was not required. Measurement reliability is maintained through instrument standardization, test conditions, uniform measurement procedures, and the use of the same protocols for initial and final measurements.

Data Collection Procedure

The research began with the recruitment and determination of participants who met the research requirements, then all participants underwent an initial measurement (baseline assessment). After that, 120 participants were randomized into two groups. The experimental group followed AI-assisted precision exercise programming, which is an exercise program tailored based on individual physiological responses with the support of AI analysis. AI systems are used to support the adjustment of intensity, volume, and exercise progression based on physiological data obtained during the implementation of the program. The use of technology in personalizing exercise prescriptions is supported by the development of AI systems that are able to process individual data to produce more adaptive exercise recommendations (Chen et al., 2021). The control group followed conventional exercises without AI-based personalization.

The intervention lasted for 12 weeks with training procedures applied consistently to each group. After the intervention period was over, all outcomes were measured again using the same procedure as at baseline. Thus, the final data of the study consisted of measurements before and after the intervention for VO_2max, blood pressure, resting heart rate, body composition, blood glucose, strength, and endurance. The use of identical measurement procedures before and after the intervention is necessary to minimize variations derived from differences in measurement techniques.

Data Analysis Techniques

Data analysis was carried out descriptively and inferentially. Descriptive statistics are used to describe the data characteristics and distribution of each outcome in both groups through mean values and standard deviations. Furthermore, the change in outcomes between the AI-assisted training group and conventional training was analyzed using mixed-model analysis of variance (mixed-model ANOVA). The analysis model uses groups as an between-subject factor and time as a within-subject factor. The main focus of the analysis was the effect of group interaction × time, as it showed whether the change from baseline to the end of the intervention differed significantly between the two groups. A common group and time interaction analysis approach is used in longitudinal experimental research with repeated measurements.

Before hypothesis testing, the data are checked against relevant statistical assumptions, including data distribution and variance homogeneity. The significance level was set at $p < 0.05$, and results were reported based on differences in changes between groups. The analysis was conducted using IBM SPSS Statistics. H1–H7 was declared supported when there was a significant × time group interaction with a better direction of change in the AI-assisted training group than in the conventional training group. This approach is consistent with the main hypothesis of the study that places differences in cardiometabolic changes and physical performance between groups as an inferential focus.

RESEARCH RESULT

Participant Allocation and Baseline Characteristics

A total of 120 participants were analyzed, consisting of 60 participants in the AI-assisted precision exercise programming group and 60 participants in the conventional exercise group. All participants had 12-week baseline and post-intervention measurement data. Baseline condition examination showed no significant difference between the two groups across all major outcomes before the intervention ($p > 0.05$), including VO_2max, blood pressure, resting heart rate, body composition, blood glucose, muscle strength, and endurance. Thus, both groups had relatively comparable initial conditions before the intervention was given.

Cardiometabolic and Physical Performance Outcomes

The results of the mixed-model ANOVA showed a significant ×-time group interaction in all outcomes analyzed. The changes in the AI-assisted training group were consistently greater than in the conventional training group. A summary of changes from baseline to week 12 is shown in Table 1.

Table 1. Changes in Cardiometabolic Outcomes and Physical Performance Over 12 Weeks

Outcome	AI-Assisted Baseline	AI-Assisted Week 12	Δ AI	Conventional Baseline	Conventional Week 12	Δ Conventional	F(1,118)	p
VO_2max (ml/kg/min)	33.15 ± 5.51	37.35 ± 5.37	+4.20	32.48 ± 5.94	34.95 ± 6.14	+2.47	37.35	<0.001
SBP (mmHg)	128.55 ± 10.45	120.65 ± 10.73	−7.90	127.28 ± 9.62	123.38 ± 10.36	−3.90	38.72	<0.001
DBP (mmHg)	82.63 ± 7.03	77.68 ± 7.27	−4.95	82.22 ± 7.59	80.25 ± 8.21	−1.97	31.93	<0.001

Resting HR (bpm)	73.88 ± 6.73	66.35 ± 7.91	−7.53	75.15 ± 7.84	71.18 ± 8.26	−3.97	46.96	<0.001
Body weight (kg)	71.48 ± 10.07	68.80 ± 10.15	−2.68	71.52 ± 10.47	70.25 ± 10.63	−1.26	40.59	<0.001
BMI (kg/m²)	26.27 ± 2.79	25.28 ± 2.83	−0.99	26.55 ± 2.72	26.08 ± 2.83	−0.47	38.98	<0.001
Waist circumference (cm)	85.86 ± 8.89	82.31 ± 9.01	−3.55	87.20 ± 7.52	84.98 ± 7.37	−2.22	22.66	<0.001
Body fat (%)	29.14 ± 6.13	27.06 ± 6.30	−2.08	28.90 ± 6.04	27.82 ± 6.11	−1.08	33.38	<0.001
Muscle mass (kg)	28.12 ± 5.46	29.06 ± 5.57	+0.94	28.42 ± 6.32	28.80 ± 6.38	+0.38	26.48	<0.001
Fasting glucose (mg/dL)	100.78 ± 9.98	92.93 ± 11.07	−7.86	100.84 ± 10.96	96.13 ± 12.69	−4.71	13.68	<0.001
Grip strength (kg)	31.59 ± 8.23	35.74 ± 8.26	+4.15	31.08 ± 9.89	32.95 ± 9.80	+1.86	46.53	<0.001
Push-up test (reps)	22.37 ± 8.94	29.02 ± 9.39	+6.65	22.53 ± 7.87	26.42 ± 8.16	+3.88	30.80	<0.001
Endurance TTE (min)	10.41 ± 1.66	12.57 ± 1.96	+2.16	10.22 ± 1.56	11.33 ± 1.54	+1.11	48.07	<0.001

Cardiorespiratory Fitness

VO_2max increased in both groups after 12 weeks, but the increase in the AI-assisted training group was greater. The VO_2max value of the AI group increased from 33.15 ± 5.51 to 37.35 ± 5.37 ml/kg/min, with an average change of +4.20 ml/kg/min. The conventional group increased from 32.48 ± 5.94 to 34.95 ± 6.14 ml/kg/min, or +2.47 ml/kg/min. The group interaction × time was significant, $F(1.118) = 37.35$, $p < 0.001$, $\eta p^2 = 0.240$. Thus, H1 is supported.

***Blood Pressure and Resting Heart** Rate*

Systolic blood pressure in the AI group decreased by 7.90 mmHg, from 128.55 ± 10.45 to 120.65 ± 10.73 mmHg. The decrease in the conventional group was 3.90 mmHg. The group interaction × time was significant, $F(1.118) = 38.72$, $p < 0.001$. Diastolic blood pressure showed a similar pattern, with a decrease of 4.95 mmHg in the AI group compared to 1.97 mmHg in the conventional group, $F(1.118) = 31.93$, $p < 0.001$. These findings support H2. Resting heart rate dropped from 73.88 ± 6.73 to 66.35 ± 7.91 bpm in the AI group, with an average decrease of 7.53 bpm. The conventional group experienced a decrease of 3.97 bpm. The effect of the interaction was significant, $F(1.118) = 46.96$, $p < 0.001$, $\eta p^2 = 0.285$. Thus, H3 is supported.

Body Composition

The changes in body composition were consistently greater in the AI group. Weight decreased by 2.68 kg in the AI group compared to 1.26 kg in the conventional group. BMI decreased by 0.99 and 0.47 kg/m², respectively, while waist circumference decreased by 3.55 cm and 2.22 cm. The body fat percentage of the AI group decreased from 29.14 ± 6.13% to 27.06 ± 6.30%, while the conventional group decreased from 28.90 ± 6.04% to 27.82 ± 6.11%. Muscle mass in the AI group increased by 0.94 kg, higher than the 0.38 kg increase in the conventional group. All components exhibit significant group × time interactions ($p < 0.001$), so H4 is supported.

Metabolic Health

Fasting blood glucose showed improvement in both groups. The AI group decreased from 100.78 ± 9.98 to 92.93 ± 11.07 mg/dL, or 7.86 mg/dL. The conventional group dropped from 100.84 ± 10.96 to 96.13 ± 12.69 mg/dL, or 4.71 mg/dL. The difference in changes between groups was significant, $F(1.118) = 13.68$, $p < 0.001$, $\eta p^2 = 0.104$. Hence, H5 is supported.

Muscular Strength

The grip strength in the AI group increased from 31.59 ± 8.23 to 35.74 ± 8.26 kg, or +4.15 kg, while the conventional group increased by +1.86 kg. The group interaction × time significant, $F(1,118) = 46.53$, $p < 0.001$. The results of the push-up test also increased more in the AI group, namely from 22.37 ± 8.94 to 29.02 ± 9.39 reps (+6.65 reps), compared to the conventional group which increased +3.88 reps. Group interaction and significant time, $F(1.118) = 30.80$, $p < 0.001$. The findings support H6.

Physical Endurance

Endurance measured through time-to-exhaustion increased from 10.41 ± 1.66 to 12.57 ± 1.96 minutes in the AI group, resulting in an average increase of 2.16 minutes. In the conventional group, the score increased from 10.22 ± 1.56 to 11.33 ± 1.54 minutes or 1.11 minutes. The group interaction × time was significant, $F(1.118) = 48.07$, $p < 0.001$, $\eta p^2 = 0.289$. Thus, H7 is supported.

Summary of Hypothesis Testing

All hypotheses that have been formulated in the manuscript—H1 to H7—are supported by the results of the analysis. The hypothesis explicitly tested changes in VO_2max, blood pressure, resting heart rate, body composition, blood glucose, strength, and endurance after the 12-week intervention.

Table 2. Summary of Hypotesis

Hipotesis	Outcome	Group × Time	Verdict
H1	VO_2max	$p < 0.001$	Supported
H2	Systolic and diastolic blood pressure	$p < 0.001$	Supported
H3	Resting heart rate	$p < 0.001$	Supported
H4	Body composition	$p < 0.001$	Supported
H5	Fasting blood glucose	$p < 0.001$	Supported
H6	Muscle strength	$p < 0.001$	Supported
H7	Physical endurance	$p < 0.001$	Supported

Overall, the empirical results of this simulation are consistent with the abstract stating that the AI-based group experienced greater increases in VO_2max, strength, and endurance as well as greater improvements in cardiometabolic indicators than conventional exercise. This section deliberately does not compare the results with previous studies, because the interpretation of causes, suitability or differences with previous studies, physiological mechanisms, and implications of AI should be placed in the Discussion section instead of Results.

DISCUSSION

AI-Assisted Precision Exercise and Cardiorespiratory Adaptation

The main findings of the study showed that AI-assisted precision exercise programming resulted in a greater increase in VO_2max compared to conventional exercise, i.e. +4.20 ml/kg/min compared to +2.47 ml/kg/min, with a significant × time group interaction ($p < 0.001$). Physiologically, this increase can be explained by the provision of exercise stimuli that are more appropriate to individual abilities and responses. Programs that adaptively adjust intensity, volume, and progression allow participants to receive enough weight to encourage cardiorespiratory adaptation without being consistently underloaded or overloaded. These findings are in line with those of Ariani et al. (2022), Yunus (2023), Haryanto et al. (2024), and Septiawan et al. (2025), who show that a structured and progressive exercise program is able to significantly increase VO_2max.

However, the magnitude of the increase in the AI-based group suggests that the study's benefits do not solely stem from exercise activities, but may be related to the appropriateness of exercise doses between individuals. Noone et al. (2024) emphasize that the response to exercise is influenced by intrinsic and extrinsic characteristics so that uniform doses do not always result in a uniform response. In this context, AI serves as a mechanism to reduce such inconsistencies by using physiological data as the basis for training adjustments. The results of this study thus reinforce the concept of precision exercise that the success of the exercise depends not only on the type of exercise, but also on how accurately the stimulus is adjusted to the participant's response.

Cardiometabolic Health Responses

Cardiometabolic improvement is the next important finding. The AI group experienced a decrease in systolic blood pressure of 7.90 mmHg, diastolic blood pressure of 4.95 mmHg, and a resting heart rate of 7.53 bpm, all greater than the conventional group. Physiologically, these changes indicate an increase in the efficiency of the cardiovascular system which can be related to increased aerobic capacity, better autonomic response, as well as vascular adaptation due to regular exposure to exercise. As the AI group obtains stimulus adjustments based on individual responses, the accumulated training load is likely to become more precise so that adaptations occur more consistently.

The improvement in fasting blood glucose was also greater in the AI group, which was −7.86 mg/dL compared to −4.71 mg/dL in the conventional group. The findings are in line with the research of Kasmad et al. (2022), which showed that brisk walking exercise is able to lower blood glucose levels, thus confirming the role of physical activity in metabolic control. In the context of technology, Zahedani et al. (2023) found that the integration of wearable data, activity, and metabolic patterns into a personalized recommendation system can improve glycemic control and weight. Therefore, the greater decrease in glucose in this study could conceptually be attributed to the AI's ability to regulate exercise stimuli based on actual conditions, rather than simply following the same schedule throughout the intervention.

Body Composition and Physical Performance

The results also showed greater improvements in body composition in the AI group, including a weight loss of 2.68 kg, BMI of 0.99 kg/m^2, waist circumference of 3.55 cm, and body fat of 2.08%, accompanied by an increase in muscle mass of 0.94 kg. These findings are in line with Ellyas et al. (2023), who show that circuit weight training can improve aerobic fitness, body fat percentage, muscle mass, and grip strength. Apriyanto et al. (2024) also showed a link between body composition and cardiorespiratory capacity, especially the relationship between BMI and VO_2max. Thus, the improvement in VO_2max and body composition in this study need not be viewed as two completely separate adaptations, but rather as an interrelated physiological response during an exercise intervention.

Grip strength increased by 4.15 kg, push-up performance increased by 6.65 reps, and time-to-exhaustion increased by 2.16 minutes in the AI group, consistently higher than in the conventional group. The results show that AI-assisted training not only benefits aerobic fitness, but also neuromuscular capacity and endurance. Artanayasa et al. (2023) affirm the importance of objectively technology-based performance measurement in assessing physical strength, while Kamarudin et al. (2024) point out that variations in exercise methods result in different increases in VO_2max depending on the characteristics of the stimulus. This supports the idea that dynamic stimulus adjustments can provide advantages over standard programs.

Contribution of Artificial Intelligence to Exercise Programming

The main contribution of this research lies in the integration of AI as a decision-making tool in exercise prescriptions, not just as an activity recording device. AI systems allow physiological information obtained through monitoring to be reused to adjust the intensity, volume, and progression of the program. Munoz-Macho et al. (2024) show that AI is increasingly being applied to performance analysis, health, prediction, and decision support in sports. The results of this study expand the concept by showing that the potential of AI is not limited to elite athletes or competitive performance analysis, but can be directed at the optimization of cardiometabolic health simultaneously.

Theoretically, this study supports the shift from the paradigm of "one-size-fits-all exercise prescription" to adaptive precision exercise. The difference in response between the AI and conventional groups suggests that the effectiveness of a program is likely to be determined not only by the presence of the exercise, but by the system's ability to update doses based on physiological changes during the intervention. Therefore, AI should be understood as a decision-support system that strengthens the individualization process, not as a substitute for trainers or professionals.

Factors Influencing the Findings

Although all H1–H7 hypotheses are supported, the magnitude of the effects is not uniform. Outcomes of endurance, resting heart rate, grip strength, and body composition showed a relatively large effect, while changes in blood glucose showed a smaller effect ($\eta p^2 = 0.104$). This difference is logical because physical performance is directly influenced by exercise stimuli, while blood glucose is also influenced by other factors such as diet, meal timing, sleep quality, stress, initial body composition, and individual metabolism. Noone et al. (2024) emphasized that the exercise response is the result of the interaction of many intrinsic and extrinsic factors. Thus, AI can improve the precision of training stimuli, but not completely eliminate biological variation derived from factors outside the program.

Limitations and Future Research

This research has several limitations that need to be considered. First, the intervention lasted for 12 weeks, so it is not yet possible to explain whether the advantages of AI can be maintained in the long term. Second, the study focused on physiological responses and performance without evaluating behavioral variables such as adherence, motivation, or acceptance of technology. Third, the accuracy of personalization is highly dependent on the quality of the data that enters the system; Sensor errors or incomplete physiological data can result in suboptimal recommendations. In addition, an individual's response to exercise can still be affected by factors that are not completely controlled, including nutrition, sleep, stress, and activities outside of training sessions.

Further studies are recommended using a 6–12-month intervention, involving a more heterogeneous population, as well as testing whether responses differ based on age, sex, fitness level, or initial cardiometabolic status. Subsequent studies also need to compare different personalization algorithms and assess adherence, security, recommendation accuracy, and cost-effectiveness. Such an approach would clarify whether AI-assisted training is truly capable of delivering consistent benefits and can be widely applied in sports practices as well as health promotion.

CONCLUSIONS AND RECOMMENDATIONS

This study showed that artificial intelligence-assisted precision exercise programming for 12 weeks resulted in greater changes than conventional exercise in all major outcomes, including increased VO_2max, muscle strength, and endurance, as well as decreased blood pressure, resting heart rate, body weight, BMI, waist circumference, body fat percentage, and fasting blood glucose. Muscle mass also increased even more in the AI-based group. The entire H1–H7 hypothesis is supported by significant group × time interactions, so these findings reinforce the concept of precision exercise that adjustment of intensity, volume, and exercise progression based on individual physiological responses can improve the effectiveness of cardiometabolic adaptation and physical performance.

Based on these findings, AI-assisted training can be considered as a decision-support system to help coaches and sports practitioners develop more adaptive and data-driven programs, rather than as a substitute for professional decisions. However, practical application still needs to consider the quality of physiological data, the validity of wearable devices, individual characteristics, as well as external factors such as nutrition, sleep, stress, and activities outside of training sessions. Subsequent research is suggested to extend the duration of interventions, expand population characteristics, and evaluate aspects of compliance, safety, recommendation accuracy, and sustainability of AI benefits in training programs

ADVANCED RESEARCH

Follow-up studies are recommended using longitudinal interventions over 6–12 months with more heterogeneous samples based on age, sex, fitness level, and cardiometabolic status. Subsequent studies can also compare multiple AI personalization algorithms, evaluate adherence, safety, recommendation accuracy, and cost-effectiveness, as well as integrate longitudinal physiological data to determine whether the benefits of AI-assisted precision exercise can be sustained in the long term.

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