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Integration of an AI-Powered Personalized Exercise Program for Enhancing Physical Fitness of Female Amateur Athletes

Mahnoor Shahid
mahnoorge27@gmail.com
M.Phil Scholar, The University of Lahore, Pakistan

Dr. Hummaira Farah
hummaira.farah@sps.uol.edu.pk
Associate Professor, The University of Lahore, Pakistan

Corresponding Author: Dr. Hummaira Farah hummaira.farah@sps.uol.edu.pk

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ABSTRACT

In resource-constrained higher-education settings, amateur athletes are often not individually prescribed exercise, limiting fitness gains through training. Recent artificial intelligence (AI) advancements provide a scalable option for generating personalized programs. However, evidence on their effectiveness in young female amateur athletes from South Asia remains limited. This study evaluated the application of an eight-week Artificial Intelligence based individualized exercise program on physical fitness of female amateur athletes of Bachelor of Science (Sports Sciences) program of Lahore, Pakistan. A group of 45 female amateur athletes (Mage = 22.78 years, SD = 2.74) were selected for a pre experimental one group pre-test post-test experiment. Baseline anthropometric data (body weight, body mass index) and physical fitness measurements, the 20m shuttle run test for cardiorespiratory fitness, modified push-up test for upper body muscular endurance, plank hold test for core endurance and sit and reach test for flexibility were collected through a structured baseline assessment sheet. A custom AI tool developed weekly personalized exercise programs based on participants' reported progress and adapted from ACSM (2022) guidelines. Same post-test measurements were conducted after 8 weeks. The data analysis was performed by means of paired-sample t-tests, Cohen's d effect sizes, and 95% confidence interval through IBM SPSS Statistics (v.26). There were significant pre-to-post improvements for all six outcome variables ($p < .001$), and all effect sizes were large ($|d| > 0.80$). The largest effect size phenomenon was observed for plank hold time ($d = 3.36$) followed by sit-and-reach flexibility ($d = 2.61$), modified push-ups ($d = 2.42$), body weight ($d = -1.85$), body mass index ($d = -1.81$) and estimated VO_2max ($d = 1.27$). A study showed that a personalized exercise program powered by Artificial Intelligence delivered significant results in several physical fitness components of female amateur athletes. The results of the study demonstrate that low cost survey driven AI personalization is feasible and effective in the Pakistani higher education context and paves the way for larger controlled trials.

Keywords: *Artificial Intelligence; Personalized Exercise Program; Physical Fitness*

INTRODUCTION

Recognised as a principal determinant of fitness, athletic performance and long-term health and wellbeing. As per ACSM (2022), physical fitness can be defined as the multidimensional ability characterized by cardiorespiratory endurance, muscular strength, muscular endurance, flexibility and body composition. In university populations, low fitness has been linked to increased CV risk, lower mental health and less academic engagement (Blair et al., 1995; Myers et al., 2002). A significant portion of the world's youth especially women in low and middle income countries was inactive and did not have access to individualised exercise prescription despite the evidence.

Amateur athletes fall into a different category in this. The term is used to refer to a nonprofessional, non-remunerated individual participating in physical activity organised sporting and who trains without continuous supervision of a full-time coach or coaching staff. University students participating in sports sciences physical education courses are likely to belong to this category: they are physically active; recreationally involved in sports such as badminton, jogging, aerobics or general fitness training; want their fitness levels improved, but do not routinely receive the individualised programming, biomechanical analysis, and continual monitoring elite athletes enjoy. The difference between standardized group exercise prescription and the heterogeneous nature of the baseline fitness, schedules and preferences of amateur athletes is well known (Garber et al., 2011) and is a major reason for suboptimal training.

New possibilities using AI and machine learning to prescribe exercise at scale to individuals have recently become a reality. AI-driven systems can take in inputs like the user's demographics, anthropometrics, baseline performance, preferences, and self-reported responses and create tailor made recommendations. Moreover, such systems adapt recommendations across training cycles. In their 2024 study, Dergaa et al. revealed that large language models can generate reasonable baseline lists of exercises for health promotion tailored to users when they critically assessed outputs from OpenAI's GPT 4 model. However, they also stressed that the outputs must always be checked against the guidelines by experts. In phase three randomized clinical trial, Mathioudakis et al. (2025) demonstrated that an AI led lifestyle intervention, guided by the Diabetes Prevention Program, was non-inferior to a human coach led version with regards to composite outcome of weight loss, physical activity and reduction in HbA1c levels. Gao et al. (2025) found that in a quasi-experimental study of 456 university students, a gamified mobile app powered by AI achieved high usability. Machine learning models have also been developed to predict daily recovery status during longer-term endurance training from individual level training, sleep and heart rate variability data (Rothschild et al., 2024).

Despite these steps forward, three key gaps remain. To begin with, most empirical evaluations have taken place in high income contexts. Samples have stemmed from elite athletes, working adults with metabolic risk, or the general university community in East Asian and North American contexts. There is a lack of evidence concerning AI driven exercise prescription in South Asia. Many existing AI exercise systems require continuous wearable sensing, computer vision analysis, or online connectivity. This is not feasible in many resource constrained colleges, where students may not reliably access such resource infrastructure. In most cases, intervention studies recruit mixed gender or male dominant samples. As such, young female amateur athletes who face added structural and cultural barriers to structured training in many South Asian settings are largely unrepresented in the literature.

The gaps are significant in the Pakistani context. According to Nishtar et al. (2013), the countrywide data indicates that there is an increasing sedentary behaviour among women aged 18 to 30 years. This has been accompanied by an increasing overweight and limited access to structured physical activity programming. The instructor to student ratios in physical education programs of colleges in Pakistan are generally high, and prescription of exercise is hardly practicable through traditional instructor led means. Simultaneously, the rapid spread of internet enabled smartphones among university students provides a realistic delivery channel for AI-mediated personalization, so long as such systems do not require continuous wearable monitoring.

In view of this, the present investigation aimed to assess the effect of an 8 week AI-enabled personalized exercise program on the physical fitness of female amateur athletes enrolled in BS (Sports Sciences) in Lahore, Pakistan. The intervention was structured for benefitting from a low resource educational context: required no wearables, no continuous internet connection for the duration of training and required no equipment other than what is available in a government college. The research question that was tested was whether female amateur athletes involved in the personalized exercise program powered by AI made statistically and practically significant progress in their cardiorespiratory fitness, muscular endurance, core stability, flexibility and body composition from pre-test to post-test.

METHOD

Research Design

In an experimental study, one group pre-test post-test design was used to determine the effect of AI-based personalized exercise programme (Creswell & Creswell, 2018). The single group design was chosen for pragmatic and ethical reasons. Due to the chosen participants being female students from the same Bachelor of Science cohort, the lack of availability of a similar comparison group meant there were no alternative options within time available. The fitness measures were the same in baseline (pre-test) and at the end of the intervention (post-test), which lasted for eight weeks.

Participants

For the study, 45 female amateur athletes were selected purposively from the BS Sports Sciences program at Government Graduate College for Women located in Township, Lahore. According to Cohen (1988), the a priori power analysis for sample size adequacy based on the assumption of a medium effect size of $d = 0.50$, $\alpha = .05$ and statistical power 0.80 indicated that a minimum of 34 subjects need to be taken for paired sample. The estimated attrition rate of 20 to 25% was accounted for in the 45 participants. The sample size also fits in with other AI-based exercise intervention studies that have shown significant fitness benefits with similar numbers.

To be included, participants must be (a) female students of BS Sports Sciences or Health and Physical Education, (b) between 18 and 27 years, (c) classified as amateur athletes according to the operational definition set forth, and (d) agreed to participate in the eight-week intervention. Participants were excluded if they had (a) any diagnosed medical ailment which precludes from engaging in moderate intensity of physical activity, (b) any musculoskeletal injury in the past six months which contraindicated structured training, or (c) already enrolled in any outside structured fitness training program.

Instruments and Measures

Using a Baseline Participant Assessment Sheet developed for this study, all measures were delivered. The sheet includes the demographic details, health screening replies, anthropometric measurement, the baseline results of fitness tests, and input parameters on AI Personalisation.

Anthropometric measures. The research team used a calibrated digital scale and stadiometer to measure the weight (in kg) and height (in cm) of the respondents. Body mass index (BMI) was calculated as weight in kilograms divided by the square of height in meters and classified according to World Health Organization (WHO, 2000) thresholds.

Cardiorespiratory fitness. To measure the cardiorespiratory fitness, the 20m multistage shuttle run test was used (Léger et al., 1988). We used standard conversion norms to derive estimated maximal oxygen consumption (VO_2max) from the final stage and shuttle achieved.

Upper body muscular endurance. As per ACSM (2022), the modified knee-supported push-up test was used to measure upper body muscular endurance. The total number of repetitions properly performed until volitional fatigue was measured.

Core muscular endurance. The front plank hold test measured core muscular endurance in young adults. The time (in seconds) that correct form could be kept was measured.

Flexibility. The sit-and-reach test measured flexibility, with the better of two trials considered the participant's score (in centimetres).

AI-Powered Intervention

In the present study the customized exercise programs were generated by a custom AI-based application which was configured for the study. For each participant, the application included a standard set of information related to (a) demographics, (b) anthropometric measurements, (c) baseline fitness scores from the four fitness tests, (d) self reported injury history, and (e) training frequency and session duration. Using this information, the system generated an eight-week personalized program with the number of sessions per week, duration of sessions, and the type, intensity, number of series, repetitions and progression rules of the aerobic, muscular endurance, core stability and flexibility exercises. As part of the operationalization of the adaptive feedback loop, each week participants re-entered their progress, perceived exertion, and discomfort into the system to generate an adapted plan for the following week. Following good practice recommendations for large language models in health applications (Dergaa et al., 2024), every AI output developed by the study team was checked by the principal investigator and verified against ACSM (2022) prior to distribution. Plans that went beyond the right intensity levels or clashed with reported injury history underwent manual moderation.

Procedure and Ethical Considerations

The research was carried out at Government Graduate College for Women, Township, Lahore, where practical space for fitness tests and basic fitness equipment was available. After the departmental review process of The University of Lahore provided ethics approval, the study strictly followed the ethics principles of the American Psychological Association (APA). Before participating in the current study, all participants were informed about the study and provided written informed consent. Participation was voluntary with a right to withdraw at any time without any consequences for the participants. Data was anonymized, kept private, and used solely for research. Throughout the data-collection period, cultural sensitivities were maintained, such as the female only assessment setting.

Statistical Analysis

IBM SPSS Statistics version 26.0 was used for analysing the data. Descriptive statistics standard deviations, frequencies and percentages were used to characterize and summarize the sample pre-test and post-test scores. The normality of the difference scores for each outcome variable was assessed by the Shapiro Wilk test as per recommendations where $N < 50$ (Field, 2018; Shapiro & Wilk, 1965). Paired sample *t*-tests were applied to assess the significance of changes in each variable from pre to post and Cohen's *d* was calculated to quantify the magnitude of change. Interpretation of effect sizes followed Cohen's (1988) conventions, where a classification of $|d| \geq 0.80$ is large. 95% confidence intervals were displayed for mean differences. The researchers established a statistical significance threshold of $p < .05$. All variables underwent further analysis using the paired *t*-test, despite some differences from normality, because of the central limit theorem and the sizeable sample size ($N = 45$) which is considered robust (Pallant, 2020; Tabachnick & Fidell, 2019; Thomas et al., 2011).

RESULTS

This part of the research presents the findings of the study in three sections: (i) the demographic characteristics of the sample, (ii) the descriptive statistics of the pre-test and post-test fitness scores, and (iii) the inferential statistics of the effect of the eight-week AI-powered personalized exercise program on each outcome variable.

Demographic Characteristics of Participants

All 45 of the participants were female, aged on average 22.78 years old (*SD* = 2.74; range = 18–27). The highest share of the sample (42.2%) belonged to the Young Adulthood (24–27 years) group, followed by Early Adulthood (21–23 years; 33.3%) and Late Adolescence (18–20 years; 24.4%). The classification according to WHO (2000) thresholds in baseline participants showed that 51.1% were Normal Weight and 48.9% were Overweight. None of the participants were under-weight or obese. The average training experience was 0.82 years (*SD* = 0.42), confirming that the sample could be identified as amateurs. The physical activities that were reported the most were recreational badminton (28.9%), beginner aerobics (20.0%), and irregular jogging (20.0%). At baseline, all participants were cleared medically to do physical activity of moderate intensity. Table 1 summarises the demographic characteristics.

Table 1

Demographic Characteristics of Participants (N = 45)

Characteristic	Category	N	%
Age Group	18–20	11	24.4
	21–23	15	33.3
	24–27	19	42.2
Pre-Test BMI Category	Normal (18.5–24.9 kg/m²)	23	51.1
	Overweight (25.0–29.9 kg/m²)	22	48.9
Primary Physical Activity	Recreational Badminton	13	28.9
	Beginner Aerobics	9	20.0
	Irregular Jogging	9	20.0
	Recreational Walking	6	13.3
	General Fitness (Beginner)	5	11.1
	Practical PE Classes	3	6.7

Note. BMI categories are based on World Health Organization (WHO, 2000) classification thresholds. Age groups are based on World Health Organization developmental stage classifications.

Descriptive Statistics: Pre-Test and Post-Test Scores

Inspection of pre-test and post-test descriptive statistics revealed a consistent pattern of improvement across all six outcome variables (Table 2). Estimated VO_2max increased from 23.10 ml/kg/min (*SD* = 5.05) at baseline to 25.34 ml/kg/min (*SD* = 4.89) at post-test. Modified push-up performance improved from 8.67 (*SD* = 3.81) to 12.07 repetitions (*SD* = 2.73), with a notable reduction in post-test variability indicating a homogenization of performance across participants. Plank hold time increased from 51.67 (*SD* = 17.43) to 65.87 seconds (*SD* = 15.16). Sit-and-reach flexibility improved from 16.78 (*SD* = 4.14) to 18.49 cm (*SD* = 3.79). Body weight and BMI decreased modestly but consistently, from 62.38 kg (*SD* = 7.27) to 62.05 kg (*SD* = 7.30) and from 24.55 kg/m^2 (*SD* = 2.46) to 24.41 kg/m^2 (*SD* = 2.47), respectively.

Table 2

Descriptive Statistics for Pre-Test and Post-Test Physical Fitness Variables (N = 45)

Variable	Pre-Test M	Pre-Test SD	Post-Test M	Post-Test SD
VO_2max (ml/kg/min)	23.10	5.05	25.34	4.89
Push-Ups (repetitions)	8.67	3.81	12.07	2.73
Plank Hold Time (sec)	51.67	17.43	65.87	15.16
Sit-and-Reach (cm)	16.78	4.14	18.49	3.79
Body Weight (kg)	62.38	7.27	62.05	7.30
BMI (kg/m^2)	24.55	2.46	24.41	2.47

Note. M = Mean; SD = Standard Deviation. Estimated VO_2max was derived from the 20-meter shuttle run using standardized conversion norms (Léger et al., 1988). The modified knee supported protocol was used for push ups. The best of two trials is used for sit-and-reach scoring.

Paired Sample t-Test Results and Effect Sizes

According to the paired sample *t*-tests, all six outcomes changed significantly from pre-test to post-test ($p < .001$; Table 3). Cohen's *d* values ranged from $|d| = 1.27$ to 3.36, all exceeding Cohen's (1988) interpretation of $|d| \geq 0.80$ as large, indicating meaningful effect magnitudes. The plank hold time showed the largest improvement ($d = 3.36$; mean increase = 14.20 sec), followed by sit-and-reach flexibility ($d = 2.61$; mean increase = 1.70 cm) and modified push-ups ($d = 2.42$; mean increase = 3.40 repetitions). Estimated VO_2max showed a significant effect ($d = 1.27$) with a mean increase of 2.24 ml/kg/min, while body weight ($d = -1.85$; mean change = −0.34 kg) and BMI ($d = -1.81$; mean change = −0.13 kg/m^2) displayed modest yet consistent decreases. The narrow 95% confidence intervals for the body composition variables show the high consistency of the directional change across participants. Overall, the results offer strong empirical evidence for the research hypothesis that the AI-powered personalized exercise program would lead to multi-dimensional physical fitness improvements in female amateur athletes.

Table 3

Paired-Sample t-Test Results and Cohen's d Effect Sizes for All Outcome Variables

Variable	Mean Diff.	95% CI	t(44)	p	d (Effect)
VO_2max (ml/kg/min)	+2.24	[1.71, 2.77]	8.51	< .001	1.27
Push-Ups (reps)	+3.40	[2.98, 3.82]	16.24	< .001	2.42
Plank Hold Time (sec)	+14.20	[12.93, 15.47]	22.55	< .001	3.36
Sit-and-Reach (cm)	+1.70	[1.51, 1.90]	17.50	< .001	2.61
Body Weight (kg)	−0.34	[−0.39, −0.28]	−12.43	< .001	−1.85
BMI (kg/m^2)	−0.13	[−0.15, −0.11]	−12.14	< .001	−1.81

Note. The post-test score is subtracted from the pre-test score. Reduction being an improvement for Body weight and BMI as negative values show. The mean difference is probably contained in the interval. Cohen (1988) classification regards $|d| \geq 0.80$ as large.

DISCUSSION

The objective of this study was to assess the influence of an 8-week AI-based personalized exercise program on the physical fitness of female amateur athletes enrolled in BS (Sports Sciences) in Lahore, Pakistan. The results indicate that there was a statistically significant improvement in all six fitness outcome variables, and all effect sizes surpassed Cohen's (1988) large effect threshold. There is strong support for the hypothesis that the AI-powered intervention would improve fitness in several domains. The subsequent discussion is contextualized against the empirical literature, the Pakistan higher-education context, and aspects of design limitations.

Cardiorespiratory Fitness

The estimated VO_2max experienced an increase from 23.10 to 25.34 ml/kg/min (d = 1.27), having a magnitude of cardiorespiratory adaptation, similar to that reported in the international literature for the moderate intensity structured aerobic training of untrained female adults (Garber et al., 2011). For females aged 18–29 years the baseline mean was classified as “Very Poor” as per standards set by (ACSM, 2022) and replicates the values (low fitness levels) found amongst Pakistani female university students (Nishtar et al., 2013). As with Blair et al. (1995) and Myers et al. (2002) evidence, small VO_2max increases (1–2 ml/kg/min) reduce cardiovascular disease risk and are clinically meaningful. The gains achieved were uniform as a result of coordination of aerobic loads with major focus on the baseline shuttle test performance and preferences of participants.

Muscular Endurance and Core Stability

The effect sizes for plank hold time (d = 3.36) and modified push-up performance (d = 2.42) were highest, and these effects were due to lower post-test variances (plank: 17.43 → 15.16 sec; push ups: 3.81 → 2.73 reps), suggesting lower scoring participants improved more than higher-scoring participants. The pattern shows a principle of diminishing returns and is in agreement with the periodization model of Bompa and Haff (2009), where the stimulus of training is pushed higher over cycles in a manner adapted to response. The extent of improvements in muscular endurance is likewise broadly consistent with usability and engagement outcomes reported for AI-supported programmes which have been undertaken in university populations (Gao et al., 2025). The use of an AI tool that can automate the individual-level periodization logic via weekly self-reported data is a tangible practical advantage in under resourced teaching settings over group prescription.

Flexibility

The average gain of 1.70 cm (d = 2.61) in sit-and-reach flexibility aligns with ACSM (2022) guidelines and is consistent with previous evidence showing that a structured flexibility programme produces real improvements in untrained adults (Garber et al., 2011). In Pakistan, the standardized syllabus of college physical education mostly focuses on fitness training and sports' categories, and flexibility programming does not get much attention for women. The current study treated the flexible component of the AI-generated plans as a 'must-have' module for all participants, which was adapted based on the baseline scores and self reported movement restrictions. The progress of all 45 participants, as well as the reduction in the standard deviation, highlights the universal aspect of AI flexibility prescriptions.

Body Composition

The decrease in body weight (0.34 kg; d = -1.85) and BMI (0.13 kg/m²; d = -1.81) were significantly different and in the same direction to body composition changes reported for short-duration AI-led lifestyle interventions (Mathioudakis et al., 2025). The absolute magnitude was small, and the effect size was large. Almost all of the 45 participants exhibited a reduction in body weight and BMI in the same direction. As far as Pakistani female college students are concerned, even a small decrease in BMI could be of public health concern over being overweight or obese which is linked with increased risk of type two diabetes, hypertension and polycystic ovary syndrome (Nishtar et al., 2013). Upcoming variations of the AI may include a nutrition module, which was developed with the help of a registered dietitian, that could enhance body composition results.

Effectiveness of AI-Powered Personalization

The study revealed that a personalized exercise program powered by artificial intelligence which does not require a wearable sensor and does not require the use of an internet connection during training can lead to significant improvements in multiple fitness outcomes. In this study, Pakistani female amateur athletes were trained for 8 weeks. The AI tool provided tailored first prescriptions, updated training loads weekly based on feedback, and guaranteed coverage of all important fitness elements (aerobic conditioning, muscle endurance, core stability and flexibility). The results build on previous work. Mathioudakis et al. (2025) have shown that an AI-powered lifestyle intervention has weight loss and physical activity outputs that are non inferior to human coaching. Gao et al. (2025) found an AI-driven gamified intervention highly usable with 456 Chinese university students. Rothschild et al. (2024) demonstrated machine learning prediction of daily recovery during prolonged endurance training. Finally, Dergaa et al. (2024) established that AI can generate reasonable baseline exercise recommendations when outputs are checked against established guidelines.

The present study provides direct evidence that works in a South Asian higher education context, shows the wearable free, survey driven personalization is possible and tests an underrepresented population young female amateur athletes living in a developing country context.

Implications for Practice in Pakistani Higher Education

The results have important consequences for the teaching of physical education and sports sciences in colleges in Pakistan. Because of high instructor to student ratios, it is frequently not possible to offer individualized exercise prescription through traditional means and thus large groups are left to follow a standard routine that is often poorly matched to baseline fitness and preferences. When paired with qualified instructors, AI tools can allow unique programming for large groups without replacing the instructor who teaches technique, supervises safety and motivates participation. As the intervention is non wearable, it is already well suited to colleges where this infrastructure does not exist. Similarly, the magnitude of fitness gains suggests that accessible, lower-cost interventions need not incur large effectiveness costs.

LIMITATIONS

There are a few limitations. To begin with, the pre-experimental, one group design does not have a control group, so it is ambiguous whether the AI-powered intervention is responsible for the improvements seen; nonspecific factors such as test retest learning and general exposure to structured training may account for some of the results. Subsequent studies should employ randomized controlled trials with active comparators to establish AI personalization's distinct efficacy. The second limitation stems from the fact that a single college in Lahore was the study sample. Furthermore, as it studies undergraduate female students, the results cannot be generalised for male athletes and other regions or with different socio economic strata and of higher level competitions. Another possible confounder for the body composition findings was that the dietary intake was not measured during the intervention. In the fourth instance, the VO_2max was not directly measured by expired gas analysis; instead, it was estimated from shuttle-run conversion norms. Therefore, there was generation of measurement error in the cardiorespiratory estimates. One limitation of this study is that factors such as psychological and motivational variables were not measured in either cohort. Future research should aim to amend these shortcomings by employing a controlled design, objective dietary assessment, criterion standard physiological measurement and psychosocial assessment of moderators.

CONCLUSION

The 8 week intervention of an AI-based personalized exercise program resulted in a statistically significant and practically meaningful effect in cardiorespiratory fitness, muscular endurance, core stability, flexibility, and body composition among 45 female amateur athletes enrolled in BS Sports Sciences in Lahore, Pakistan. Each of the effect sizes exceeded Cohen's threshold for a large effect, with core endurance having the largest improvement. The training did not require any wearable or internet devices always, indicating its usability in high education settings with resources. The results provide preliminary empirical support for the implementation of AI-aided exercise prescription in college physical education classes in Pakistan as traditional instructor-led approaches seldom permit personalized programming. To confirm the effects and disentangle the roles of AI personalization and systematic training exposure, future study should use a randomized controlled design and active comparator and employ longer follow up and wider demographic sampling.

Conflict of Interest

The author declares no conflict of interest.

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