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Research Article

The effect of a data analytics-based coaching model on volleyball serve accuracy among adolescent student-athletes

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This study investigated the effect of a data analytics-based coaching model on volleyball serve accuracy among adolescent male student-athletes. Forty male volleyball players aged 15–18 years were randomly assigned to either an experimental group or a control group. The experimental group participated in an eight-week coaching intervention incorporating statistical performance analysis, biomechanical evaluation through a Convolutional Neural Network–Long Short-Term Memory model based motion analysis system, and personalized feedback, whereas the control group received traditional coaching without data analytics. Serve accuracy was assessed using the American Alliance for Health, Physical Education, Recreation and Dance Volleyball Serve Test before and after the intervention. The data were analyzed using independent-samples t-tests and analysis of covariance, with Cohen's d calculated as an effect size. The findings showed that the experimental group demonstrated significantly greater improvement in serve accuracy than the control group, with a large effect size. These findings indicate that a data analytics-based coaching model may enhance volleyball serve accuracy more effectively than traditional coaching. However, the results should be interpreted in relation to the combined components of the intervention and the specific characteristics of the study sample.

Keywords: Augmented feedback; Data-informed coaching; Motor learning; Performance analytics; Volleyball serve; Youth athletes

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1. Introduction

Contemporary volleyball as a sport has also seen significant evolution due to the emergence of technology in training along with data analysis (Salim et al., 2024). Serve is one of the key elements of skills of contemporary athletes and has a vital impact on the success of the team since not only does it initiate the game but also serves as an offensive element to score points (Pawlik et al., 2024). Successful serve is what allows teams to test their opponents' defense and create a particular rhythm of the game (Ciuffarella et al., 2013). In this regard, improve in serve accuracy is the main aim in the training process because of its ability to quickly change score dynamics and the mental state of opponents (Mardila et al., 2024). Without sufficient accuracy, there is no possibility to exploit the attacking potential of serve and build effective initial attacks (Moy et al., 2024).

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Modern technologies have created some new possibilities for training methods. The International Volleyball Federation [FIVB] through its Volleyball Empowerment initiative has already started implementing data analytical tools such as Data Volley and video analysis system, which will help to develop a data-driven training process (Mroczek & Pawlik, 2023). These systems help to have in-depth knowledge of statistics of players, tactics of opponents, and game patterns, which was hard to find out without technology (Accornero et al., 2025). Thus, using technology coaches can objectively evaluate athletes' performance (Sousa et al., 2023). It means the paradigm shift from traditional training that is based on coaches' subjective observations to data-driven training management.

Despite the increasing availability of performance-analysis technologies in sport, observation-based coaching and verbal feedback remain central components of many training environments. Although such feedback is valuable for skill acquisition, relying primarily on unaided observation and general verbal comments can limit the precision and systematic nature of performance evaluation. In complex motor skills such as the volleyball serve, coaches may find it difficult to attend simultaneously to multiple movement characteristics, whereas augmented visual and technology-supported feedback can make otherwise difficult-to-detect aspects of performance more accessible for analysis (Anderson et al., 2019). A further limitation concerns feedback specificity. General verbal comments may provide athletes with insufficient information about precisely which aspects of their performance require adjustment, while specific and high-quality feedback is more conducive to identifying areas for improvement (Davor et al., 2026). Technology-supported performance analysis can additionally provide objective and data-driven information that helps learners identify strengths and weaknesses and translate feedback into targeted adjustments (Fitriati & Williyan, 2025). Similar evidence from technology-enhanced learning environments indicates that immediate feedback and performance analytics offer advantages over feedback that is delayed or less specific (Ghaemi & Bahrami, 2025). Accordingly, the absence of systematically recorded performance data may also make it more difficult for coaches and athletes to monitor changes across training sessions and evaluate progress consistently.

Athletes may face several difficulties when learning to modify their serving technique. The serve is a complex motor skill that requires the coordinated timing of multiple movement components, and attempts to modify technique may therefore place considerable demands on athletes' attentional resources. Because attention is limited, consciously monitoring several aspects of a movement simultaneously can make the process of skill modification more demanding, particularly when augmented feedback is insufficiently specific or does not provide athletes with clear information about how their movement should be adjusted (Magill & Anderson, 2017). Evidence from technology-supported learning environments similarly indicates that timely and specific feedback can facilitate error identification and subsequent correction, whereas delayed feedback may restrict opportunities for immediate adjustment (Dorji et al., 2026). Another difficulty is that athletes cannot directly view their complete movement pattern while executing the serve. Recording and subsequently analyzing performance can provide an external perspective that supports more objective self-evaluation and helps performers identify specific aspects requiring improvement (Fitriati & Williyan, 2025). In sports and physical-education settings, systematic measurement has likewise been shown to provide a useful basis for monitoring athletes' performance over time (Ulupınar & Özbay, 2020).

The combination of outcome data and movement data is supposed to facilitate the process of learning through several channels. On one hand, outcome data (knowledge of results) is a source of information about the effectiveness of the serve (accuracy score, speed, location, etc.). At the same time, movement data (knowledge of performance) provides information about the quality of movement patterns themselves (arm angle, trunk rotation, contact point, etc.). Thus, athletes are able to understand how certain parameters affect the performance result and use them to facilitate the motor learning (Magill & Anderson, 2017; Wulf et al., 2010). In this regard, the combination of movement and outcome data matches well with the principle of augmented feedback according to which feedback that is precise, specific, and timely helps athletes to acquire skills effectively (Schmidt & Lee, 2023).

Personalized feedback may offer advantages over general feedback because individual performers can differ in their technical profiles, error patterns, and areas requiring improvement. A uniform feedback approach may therefore overlook individual performance needs, whereas personalized feedback can direct attention toward the specific aspects of performance that require adjustment. Evidence from skill-learning contexts indicates that individualized and detailed feedback can help learners identify their strengths and weaknesses, clarify areas for improvement, and engage more actively in subsequent correction (Fitriati & Williyan, 2025). Data-driven and task-specific feedback can further support learners in identifying errors, monitoring their progress, and making more targeted adjustments to their performance (Dorji et al., 2026; Ghaemi & Bahrami, 2025). Applied to volleyball training, this suggests that feedback based on an athlete's own performance data may allow coaches to focus corrective instruction on the movement components that most require improvement rather than providing the same general corrections to all athletes.

It is known that service distance variation exercises positively influence serve accuracy (Ruslan et al., 2021). However, it is still general because the exercises do not take into account athletes' personal characteristics (arm strength, body rotation angle, etc.). Besides, there is evidence that video feedback improves skill acquisition in volleyball (Ghorbanzadeh et al., 2017). Artificial intelligence systems with Convolutional Neural Network–Long Short-Term Memory [CNN-LSTM] architectures show great results in recognizing and classifying movements (Wu & Wang, 2025). However, there are no studies on combining these technologies into a single model.

As shown in the Defense System Optimizer [DSO] model introduced by Davila et al. (2025), analytical data may be systematically used to optimize the defensive position of players according to their performance. In addition, such an approach may be implemented in serve development in order to use biomechanical data and performance statistics for creating particular recommendations for individual training. Nevertheless, so far, there is a lack of research on the application of coaching management models involving different types of analytical data to enhance serve accuracy. The majority of previous studies concentrate on individual technical issues while omitting data management and analysis during training. Table 1 represents a comparative analysis of previous interventions dealing with technology-enabled volleyball training and the gaps being filled in the current research.

Table 1
Comparison of Previous Interventions and Current Study

Study	*Participants*	*Technology*	*Feedback Type*	*Duration*	*Limitation*
Ruslan et al. (2021)	Volleyball athletes	None	General verbal feedback	6 weeks	No technology integration; general approach
Ghorbanzadeh et al. (2017)	Volleyball athletes	Video recording	Video feedback	8 weeks	Single technology; no biomechanical analysis
Salim et al. (2024)	Volleyball players	Wearable sensors	Performance metrics	Not specified	No intervention component
Wu and Wang (2025)	General population	CNN-LSTM system	Movement classification	N/A	Not volleyball-specific; no training intervention
Current Study	Adolescent volleyball players (15–18 years)	Data Volley + CNN-LSTM AI + personalized feedback	Multi-modal: statistical, biomechanical, individualized	8 weeks	Combined intervention; no dismantling design

The combination of statistical analysis of performance, biomechanical analysis, and personalized coaching feedback has practical implications which go far beyond investigations into single technologies. Previous literature has not analyzed these elements together and, hence, it is unclear whether an integration of all three components results in better learning gains than conventional coaching or isolated components do. In theory, there is no doubt that an integration of all three components leads to higher learning gains as it considers several factors influencing performance at once – outcome knowledge (statistical analysis), movement quality (biomechanical analysis), and personalized corrective feedback.

The current study fills some of these gaps by investigating the influence of a comprehensive data-analytics-based coaching model on serve accuracy of volleyball among adolescents. This study seeks to investigate the degree to which an eight-week training program based on data-analytics increases serve accuracy in comparison to conventional coaching among adolescent males. The primary hypothesis is that the intervention group will demonstrate significantly greater improvements in serve accuracy compared to the control group.

2. Methods

2.1. Research Design

This A randomized pretest-posttest control group design was used in this study to measure the effects of the intervention on the improvement of the serve accuracy, controlling for external factors. 40 students-athletes meeting the inclusion criteria for this study were randomly allocated into two groups: experimental (n = 20) and control (n = 20). Randomization was done by means of computer-generated numbers (Microsoft Excel RAND function). Sequentially numbered, opaque, sealed envelopes prepared by an independent researcher, who was not engaged in the process of recruiting participants and conducting interventions, were used in order to keep allocation concealment. Stratification was not performed due to a small number of participants. Participant and coach blinding was not possible due to the type of the intervention; however, assessor blinding was ensured.

Participants of the experimental group were provided with a data-analytics-based coaching model that included performance analysis by means of statistics, biomechanical assessment with the use of CNN-LSTM-based motion analysis system, and personalized feedback. Participants of the control group were subjected to traditional training approaches, including serves' repetitions starting from behind the end line, verbal correction of faults by coaches using their visual perception, and general feedback without the use of data analytics. Training programs in both groups lasted for 8 weeks (three times a week for 90 min each time) and were identical in terms of duration and frequency of interventions.

2.2. Participants

A total of 40 young male volleyball players, who were taken from different clubs in the Central Java area, participated in this experiment; their age varied between 15 and 18 years (M = 16.4 years, SD = 1.1 years). Such age group was chosen since it was an important phase of technical and tactical skills development of the athletes, which included proper and consistent serving skills. At this stage, athletes had enough physical maturity to participate in intensive training sessions using data, but they still could adapt to new movement pattern adjustments.

Inclusion criteria were: (1) three or more training sessions per week, (2) two or more years of sports experience, (3) signed informed consent of a parent or guardian, (4) willingness to go through all stages of intervention procedure, and (5) lack of participation in technology-enhanced training program within the last six months.

Exclusion criteria were: (1) presence of musculoskeletal injuries of the shoulder, elbow or wrist which prevent full serve execution, (2) missing more than 20% of all training sessions, and (3) insufficient data collection at pretest or posttest phases.

Sample size was calculated by an a priori power analysis conducted with G*Power software (Erdfelder et al., 1996). Assuming the large effect size (d = .80), α = .05, and power = .80, the minimal sample size per group required to conduct independent samples t-test is 21. In view of practical restrictions of the research, 20 participants were recruited per group. Such a sample size has enough power to identify large effects, but not medium effects or subgroup analysis according to playing positions. Table 2 presents the demographic characteristics and baseline measurements.

Table 2
Demographic Characteristics and Athlete Baseline

Characteristics	*Experimental Group (n = 20)*	*Control Group (n = 20)*	*p*
Age (years)	16.35 ± 1.12	16.45 ± 1.08	.776
Height (cm)	178.45 ± 5.23	179.10 ± 5.45	.698
Body Weight (kg)	68.75 ± 6.12	69.20 ± 6.34	.821
Experience (years)	3.65 ± 1.08	3.70 ± 1.12	.887
Training Frequency (times/week)	3.85 ± 0.49	3.90 ± 0.45	.734

Independent samples *t*-test results showed no significant differences between groups on any baseline characteristic ($p > .05$), indicating initial equivalence.

2.3. Procedure

2.3.1. Intervention protocol

The intervention took place over eight weeks (see Table 3), at a rate of three sessions per week, for a total of 24 training sessions. Each session lasted 90 minutes. All activities were done in volleyball courts, and all procedures were identical for both groups. The intervention procedures were meant to be replicable, including objectives per week and activities.

Table 3
Weekly Intervention Objectives

Week	*Experimental Group Focus*	*Control Group Focus*
1	Baseline assessment; introduction to data analytics system	Baseline assessment; basic serve technique review
2	Data collection; individual movement analysis	Serve repetition drills; general verbal correction
3	Biomechanical feedback (arm angle, contact point)	Serve repetition drills; general verbal correction
4	Statistical feedback (accuracy patterns, target areas)	Serve repetition drills; general verbal correction
5	Integrated feedback (biomechanical + statistical)	Serve repetition drills; general verbal correction
6	Goal setting based on data; targeted practice	Serve repetition drills; general verbal correction
7	Advanced feedback integration; match-situation serves	Serve repetition drills; general verbal correction
8	Posttest assessment; consolidation	Posttest assessment; consolidation

During each experimental group training session, a structured protocol of events took place in accordance with the following schedule: 15 minutes – warm-up period which involved both general and specific preparation; 40 minutes – serves practice, during which athletes executed serves and at the same time, their performance statistics were recorded using Data Volley software and CNN-LSTM motion analysis technology; 20 minutes – data review and feedback period during which athletes were able to view their performance data in conjunction with their coach and received personalized feedback based on data analysis; 15 minutes – specific technical training, during which athletes applied specific technical modifications obtained during data analysis.

Feedback in the experimental group was individualized for each training session and included specific technical suggestions based on athletes' performance data from the previous session. Athletes were provided with their biomechanical parameters (arm angle, trunk rotation, contact point height) along with their performance outcome statistics (accuracy, speed, serve location).

Feedback was delivered in a multimodal format of verbal instructions and visual data presentation (graphs, still images with motion markers). Coaches of the experimental group had three hours of training on working with data analytics systems and making evidence-based coaching decisions.

The training protocol of the control group involved serving exercise in accordance with the traditional approach, such as varying serve distance exercises and feedback from the coach based on visual observations. Feedback in the control group was verbal and provided during and after the training sessions, included general technical corrections ("toss higher", "swing faster", "follow through"). Coaches of the control group were experienced volleyball coaches with no training in data analytics.

2.3.2 AI system description

The CNN-LSTM model in this study is an in-house developed model as opposed to a commercial software and the structure involved input of video recordings of serve execution captured by two high-speed cameras (resolution 1300 × 1024; fps 60) placed at 90° and 45° to the sagittal plane and calibrated by a checkerboard pattern; data processing included video data analysis by CNN to obtain features and further processed by an LSTM network to model the temporal sequence, the CNN-LSTM model trained on a dataset of 5,000 videos of volleyball serve (3,000 training, 1,000 validation, 1,000 test videos) of 30 different volleyball players that did not take part in the current study to predict four parameters of interest – arm angle at ball contact, trunk rotation angle, contact point height, and follow-through trajectory, where the CNN-LSTM model showed 92.3% accuracy on the validation dataset in predicting these parameters against manual marker tracking. finally, in the current study, outputs of the model were evaluated by the coach for reasonableness and any changes in output values made when outputs clearly did not match the observed motion patterns, and also, the system provided quantitative biomechanical reports for each serve, emphasizing deviations from optimal parameters and areas in need of work.

2.3.3 Control condition and causal interpretation

There were differences between the experimental and the control conditions with regard to feedback specificity, personalization, and instruction. Thus, this study is unable to attribute the effects on the learning process solely to analytics or to AI, since they were intertwined with the effects of improved coaching.

2.4. Instruments

2.4.1. American Alliance for Health, Physical Education, Recreation and Dance Volleyball Serve Test

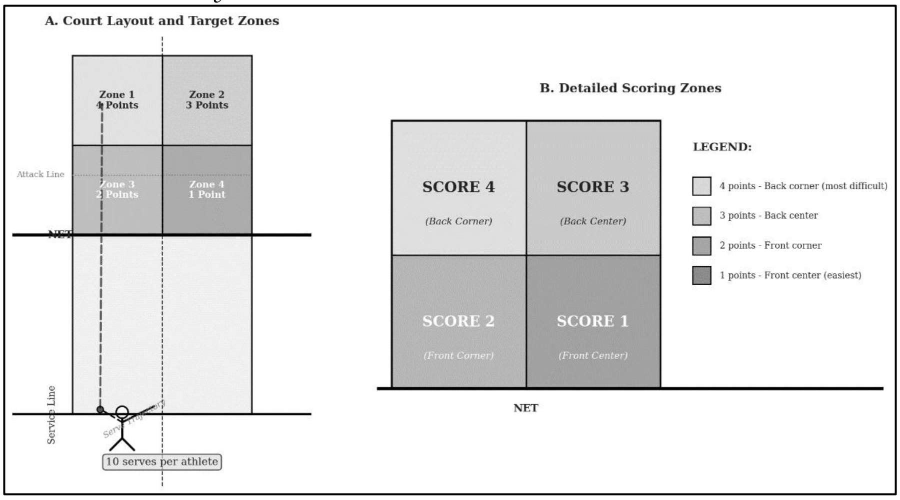
Serve accuracy measurement was done by means of American Alliance for Health, Physical Education, Recreation and Dance [AAHPERD] Volleyball Serve Test (Novianingsih & Irianto, 2019). The standardized tool possesses a high level of content validity (.89) and test-retest reliability (.91) among similar subjects. The process of measuring involved a requirement for athletes to hit 10 times with their serves the area previously marked out as the target area from the standard service area (area behind the end line).

The scoring procedure depends on the accuracy of hitting the target zone, and involves four regions having different levels of points. Back corner of the court has been assigned the highest point of 4 points, since it is the hardest to reach area for the receiver. Back center zone has 3 points, front corner – 2 points, while the front center zone, which is the easiest to reach one, got 1 point (see Figure 1). Total serve accuracy score is the sum of all accumulated points for 10 serves.

2.4.2. Measurement administration

The serve tests were performed by two assessors, blind to the assignment of the groups. The assessors underwent four hours of training on how to conduct and score the tests. The inter-rater reliability in this study was high (ICC = .94, 95% CI [.88, .97]). The assessors were placed at the opposite sides of the court to ensure that they do not miss any ball contact point and landing point.

Figure 1
AAHPERD Volleyball serve test instrument



The testing process was video-recorded to ensure quality. The measurement reliability in the current study (Cronbach's α = .92 for pretest, .93 for posttest) was similar to the reliability reported before.

The weekly measures presented in Table 8 were done during the regular training process rather than pretest/posttest measures. During each week, athletes served 10 balls under the same conditions as in pretest/posttest tests, with scores collected for development tracking.

2.5. Data Analysis

Data analyses were done using the statistical software package SPSS version 26.0 at a significance level of α = .05, where the first step involved preliminary analyses consisting of normality testing using Shapiro-Wilk test and homogeneity of variance testing using Levene's test to satisfy the assumptions of parametric tests, and the second step involved the main analysis which used ANCOVA with pretest serve accuracy score as a covariate to analyze posttest serve accuracy scores since this test will address pre-test differences and will yield more accurate estimations of the intervention effect by testing the group × time interaction where group (experimental vs. control) is a fixed factor; the secondary analyses involved paired samples *t*-tests to test within group differences between pretest and posttest scores and independent samples t-tests to test the differences between groups based on their gain scores, and effect sizes were determined using Cohen's *d* and effect sizes were interpreted as small (.2), medium (.5), and large (.8) effects (Cohen, 1988); exploratory subgroup analyses based on playing positions were carried out using one-way ANOVA with group and playing position as factors, but the findings from these tests should be interpreted carefully because they are exploratory and because of small subgroup sample sizes (4-6 per group and per playing position); no participants were excluded due to missing data, as all 40 participants finished the intervention and posttest testing.

3. Results

Descriptive statistics were first examined to characterize serve accuracy in both groups before and after the eight-week intervention. As shown in Table 4, the experimental and control groups had nearly identical pretest means (18.75 and 18.90, respectively), indicating similar baseline performance. Although serve accuracy increased in both groups at posttest, the increase was substantially greater in the experimental group, whose mean rose to 27.30 compared with 22.15 in the control group. The medians and standard deviations show a similar descriptive pattern.

Figure 2 visually compares the pretest and posttest serve accuracy scores of the two groups. The bars show that the groups started from almost the same level, whereas their posttest scores

Table 4
Descriptive Statistics of Serve Accuracy Scores

Groups and Measurement	*N*	*Mean*	*Median*	*SD*	*Min*	*Max*	*Range*
Experimental							
Pretest	20	18.75	18.5	2.34	15	23	8
Posttest	20	27.30	27.5	2.68	23	32	9
Control							
Pretest	20	18.90	19.0	2.41	15	24	9
Posttest	20	22.15	22.0	2.59	18	27	9

diverged after the intervention period. The experimental group displays a markedly larger increase than the control group, providing a visual overview of the descriptive change reported in Table 4.

To examine the posttest scores beyond group means, Figure 3 presents their distributions using boxplots. The experimental-group distribution is visibly shifted upward relative to the control group, while the box-and-whisker elements display the spread and central tendency of scores within each group. This visual comparison complements the descriptive statistics by showing how the posttest scores are distributed rather than relying only on group averages.

Figure 2
Comparison of Serve Accuracy Scores Pretest vs. Posttest

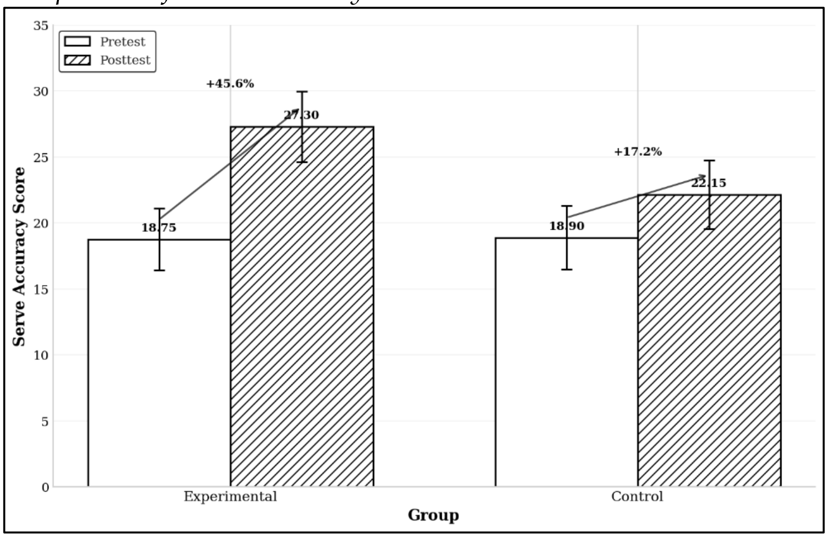
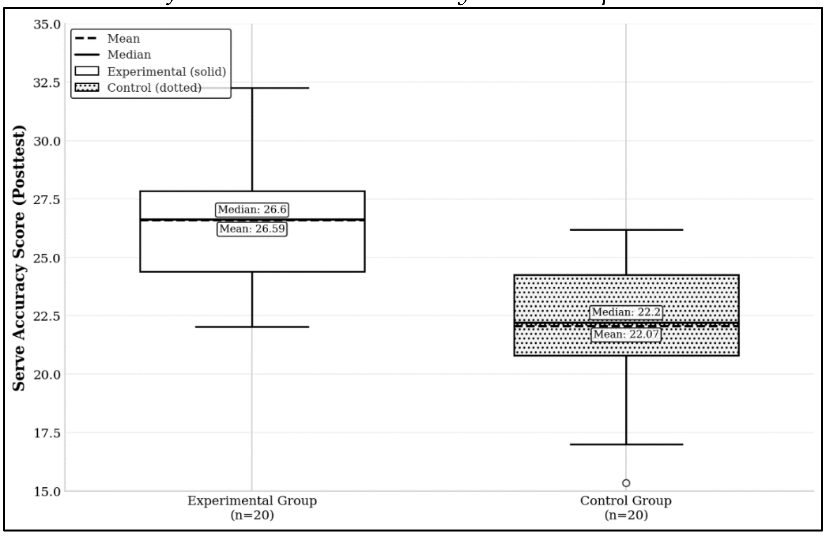


Figure 3
Distribution of Posttest Serve Accuracy Scores: Experimental vs. Control



Before testing the intervention effects, the distributional assumptions for the parametric analyses were examined. Table 5 reports the Shapiro-Wilk statistics for the pretest and posttest scores in both groups. None of the tests reached statistical significance (p values ranging from .214 to .465), indicating no evidence of substantial departures from normality and supporting the use of the planned parametric analyses.

Table 5
Normality Test Results (Shapiro-Wilk)

Groups and Measurement	*Statistic*	*df*	*Sig. (p)*	*Description*
Experimental				
Pretest	.945	20	.287	Normal
Posttest	.951	20	.389	Normal
Control				
Pretest	.938	20	.214	Normal
Posttest	.956	20	.465	Normal

The homogeneity-of-variance assumption was also evaluated before the between-group comparisons. As reported in Table 6, Levene's tests were non-significant for both the pretest, F = 0.08, p = .782, and the posttest, F = 0.21, p = .654. These results indicate that the group variances were sufficiently comparable for the subsequent analyses.

Table 6
Results of Variance Homogeneity Test (Levene's Test)

Measurement	*F*	*df1*	*df2*	*p*	*Description*
Pretest	.08	1	38	.782	Homogeneous
Posttest	.21	1	38	.654	Homogeneous

Within-group changes from pretest to posttest were examined using paired-samples t-tests. Table 7 shows that serve accuracy increased in both groups over the eight-week period. The experimental group exhibited a mean increase of 8.55 points (45.6%), whereas the control group increased by 3.25 points, indicating that the magnitude of improvement was considerably greater under the data analytics-based coaching model.

Table 7
Paired-Samples t-Test Results

Groups	*Pretest Mean*	*Posttest Mean*	*Mean Difference*	*SD Difference*	*t*	*df*	*p*	*Increase (%)*
Experimental	18.75	27.30	8.55	2.51	15.234	19	<.001	45.6
Control	18.90	22.15	3.25	2.14	6.789	19		

Between-group comparisons were then conducted to determine whether the two groups differed at baseline, at posttest, and in their gain scores. As shown in Table 8, the groups did not differ at pretest (mean difference = −0.15, p = .842, Cohen's d = .06), confirming comparable

Table 8
Independent Samples t-Test Results

Groups	*Pretest Mean*	*Posttest Mean*	*Mean Difference*	*SD Difference*	*t*	*df*	*p*	*Increase (%)*
Experimental	18.75	27.30	8.55	2.51	15.234	19	<.001	45.6
Control	18.90	22.15	3.25	2.14	6.789	19		
Measurement	*Experimental Mean*	*Control Mean*	*Mean Difference*	*SE Difference*	*t*	*df*	*p*	*Cohen's d*
Pretest	18.75	18.90	-0.15	0.75	−0.20	38	.842	.06
Posttest	27.30	22.15	5.15	0.83	6.187	38	<.001	1.84
Gain Score	8.55	3.25	5.30	0.75	7.067	38	<.001	2.26

starting levels. In contrast, the experimental group scored higher at posttest (mean difference = 5.15, $p < .001$, $d = 1.84$) and demonstrated a larger gain score (mean difference = 5.30, $p < .001$, $d = 2.26$), with both effects exceeding the conventional threshold for a large effect.

Primary ANCOVA analysis: After controlling for pretest serve accuracy, the experimental group demonstrated significantly higher posttest serve accuracy compared to the control group, $F(1, 37) = 38.27$, $p < .001$, partial $\eta^2 = .51$. The adjusted mean difference was 5.15 points (95% CI [3.46, 6.84]), representing a large intervention effect.

To complement the mean-based analyses, Table 9 describes how participants were distributed across improvement categories. In the experimental group, 70% of participants were classified in the high or very high improvement categories, compared with 10% in the control group. In contrast, most control-group participants were concentrated in the medium, low, or very low categories. Because these category thresholds were created for descriptive purposes and have not been empirically validated, the distribution should be interpreted as a descriptive illustration of the observed gains rather than as an additional inferential test.

Table 9

Frequency Distribution of Serve Accuracy Improvement Categories

Improvement Category	*Criteria*	*Experimental Group*		*Control Group*	
		n	*%*	*n*	*%*
Very High	>60%	3	15	0	0
High	41-60%	11	55	2	10
Medium	21-40%	5	25	8	40
Low	11-20%	1	5	6	30
Very Low	0-10%	0	0	4	20
Total		20	100	20	100

Note. Improvement category thresholds are descriptive only and lack empirical validation. These categories should be interpreted cautiously.

Weekly descriptive scores were examined to illustrate how serve accuracy developed across the intervention period. Table 10 shows that the groups were nearly equivalent in Week 1, with a difference of only 0.2 points, but the gap increased progressively across subsequent weeks. By Week 8, the experimental group reached a mean of 27.30 compared with 22.15 in the control group, corresponding to a 45.6% improvement from the experimental group's baseline. These weekly values are descriptive and were not subjected to inferential testing.

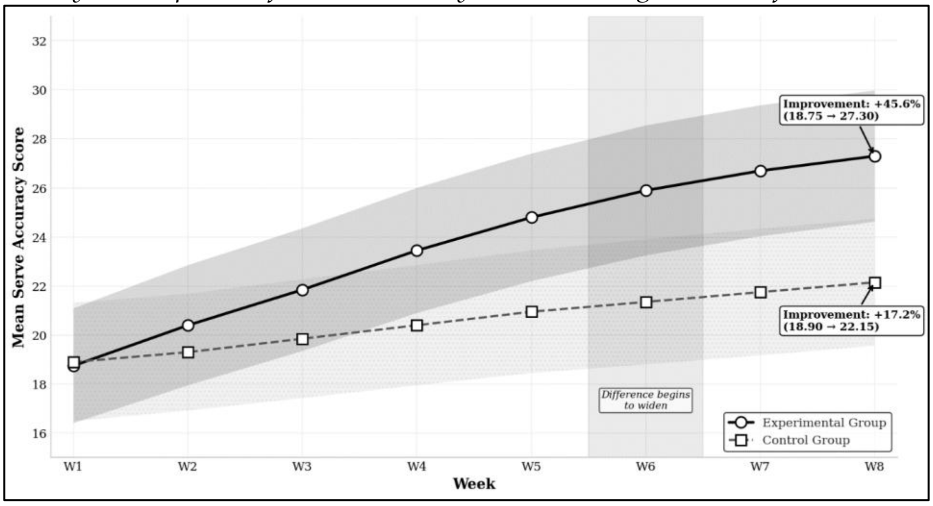
Table 10

Average Serve Accuracy Development Per Week

Week	*Experimental Group (Mean ± SD)*	*Control Group (Mean ± SD)*	*Difference*	*% Improvement (Experimental)*
1	18.75 ± 2.34	18.90 ± 2.41	−0.2	–
2	20.40 ± 2.45	19.30 ± 2.38	1.1	8.8
3	21.85 ± 2.50	19.85 ± 2.42	2.0	16.53
4	23.45 ± 2.55	20.40 ± 2.45	3.05	25.07
5	24.80 ± 2.60	20.95 ± 2.50	3.85	32.27
6	25.90 ± 2.65	21.35 ± 2.55	4.55	38.13
7	26.70 ± 2.67	21.75 ± 2.58	4.95	42.4
8	27.30 ± 2.68	22.15 ± 2.59	5.15	45.6

The pattern of change across the eight weeks is illustrated in Figure 4. Both groups show an upward trajectory, but the slope of improvement is visibly steeper for the experimental group, and the separation between the two groups becomes progressively larger as the intervention proceeds. The figure is intended to visualize the descriptive weekly trend reported in Table 10 and should not be interpreted as evidence of statistically significant week-by-week differences.

Figure 4
Weekly Development of Serve Accuracy Scores During 8 Weeks of Intervention



Exploratory subgroup analyses were conducted to describe whether the pattern of improvement was similar across playing positions. As presented in Table 11, the experimental group showed larger mean gains than the control group for servers, opposites, outside hitters, and middle blockers, with between-group differences ranging from 5.00 to 5.60 points. Although the reported *p*-values were below .05 for each position, the subgroup sizes were very small (4–6 participants per group) and multiple comparisons were conducted without correction; therefore, these findings should be regarded as exploratory rather than confirmatory.

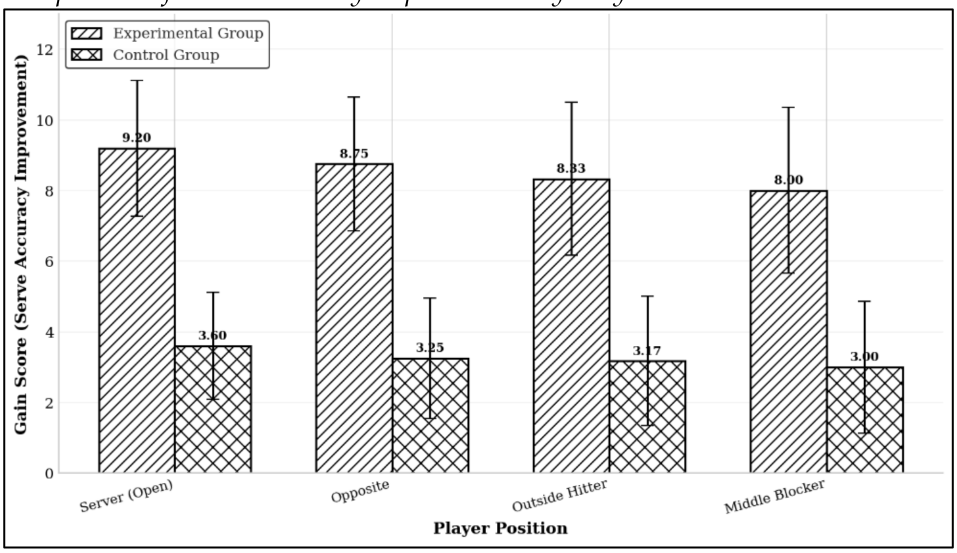
Table 11
Comparison of Serve Accuracy Improvement by Position (Exploratory)

Position	*n*	*Experimental Group (Gain)*	*n*	*Control Group (Gain)*	*Difference*	*p*
Server (Open)	5	9.20 ± 1.92	5	3.60 ± 1.52	5.6	.001
Opposite	4	8.75 ± 1.89	4	3.25 ± 1.71	5.5	.004
Outside Hitter	6	8.33 ± 2.16	6	3.17 ± 1.83	5.16	.003
Middle Blocker	5	8.00 ± 2.35	5	3.00 ± 1.87	5.0	.008

Note. These analyses are exploratory. Results should be interpreted cautiously due to small sample sizes in each subgroup and multiple comparisons without correction.

Figure 5 provides a visual comparison of gain scores across the four playing positions.

Figure 5
Comparison of Serve Accuracy Improvement by Player Position



For every position, the experimental group shows a larger average improvement than the corresponding control group, and the size of the between-group difference appears relatively consistent across positions. The error bars also illustrate variability within the small subgroups. Consistent with Table 11, these patterns are exploratory and should be interpreted cautiously because of the limited number of participants in each position.

Table 12 provides an integrated summary of the statistical tests used to evaluate the study hypotheses. The paired-samples tests indicated significant pretest-posttest changes in both the experimental and control groups, while the ANCOVA showed a significant posttest difference after adjustment for baseline serve accuracy. The independent-samples comparison of gain scores also favored the experimental group. Accordingly, the null hypotheses corresponding to H1-H4 were rejected, and the substantive hypotheses were supported.

Table 12
Summary of Hypothesis Tests

Hypothesis	*Statistical Test*	*Results*	*Decision*
H1: There is a difference in pretest-posttest scores of the experimental group	Paired-samples *t*-test	$t = 15.234$, $p < .001$	Supported
H2: There is a difference in pretest-posttest scores of the control group	Paired-samples *t*-test	$t = 6.789$, $p < .001$	Supported
H3: There is a difference in posttest scores between experimental and control groups	ANCOVA	$F(1,37) = 38.27$, $p < .001$	Supported
H4: There is a difference in gain scores between experimental and control groups	Independent samples *t*-test	$t = 7.067$, $p < .001$	Supported

4. Discussion

4.1. Effectiveness of the Data-Analytics-Based Coaching Model

The findings of the current study indicate a substantially greater improvement in serve accuracy among athletes who received data analytics-based coaching. The experimental group increased its serve accuracy score by 45.6%, from 18.75 to 27.30, whereas the control group improved by 17.2%, from 18.90 to 22.15. This pattern suggests that integrating data analytics into the training process may accelerate the development of serve accuracy by providing athletes and coaches with more systematic and performance-specific information for technical adjustment. This interpretation is compatible with evidence from technology-enhanced learning showing that personalized, data-informed feedback can help learners identify specific performance components requiring improvement and direct their efforts accordingly (Fitriati & Williyan, 2025). The use of video and technology-supported feedback has likewise been identified as a potentially valuable component of mentoring and coaching practices in exercise and sport sciences (Özkara, 2025). Systematic performance analysis is also well established as a means of identifying meaningful variations in volleyball performance. García-de-Alcaraz and Marcelino (2017), for example, demonstrated that technical-tactical performance indicators, including serve performance, vary according to match quality and competition level, illustrating the value of systematic analysis for coaches when evaluating performance and designing training plans. Their study, however, was observational and examined match performance rather than the effects of a data analytics-based training intervention. Therefore, the present findings extend this line of work by providing evidence that analytics-informed feedback may also contribute to the development of serve accuracy during the training process.

Effectiveness of the intervention is reflected in very large effect size (Cohen's d=1.84 for the posttest differences between groups) calculated according to Cohen's (1988) criteria. The size of effect in the current study exceeded the size of effect (0.97) obtained by Ghorbanzadeh et al. (2017) in the study investigating the effect of the video feedback-based intervention on serving skills. This difference may be explained by the multi-component character of the intervention in the current study, which included the application of statistics, biomechanics, and personalized feedback. This combination of components may lead to synergistic effects that are impossible to achieve with one component only, which is mentioned by Kunavar et al. (2024). Learning complex motor skills requires precise and specific feedback, which is provided within multi-component intervention.

However, the design of the current research does not allow determining the contributions of particular intervention components. Intervention was applied as the bundle of components, and experimental and control groups differed not only in the application of technology but also in the provision of more precise and personalized feedback. Thus, the effect of the intervention can be identified, but the contribution of particular components to the effect cannot be determined.

4.2. Interpretation of Performance Gains

The observed improvements should primarily be interpreted as gains in performance under the conditions assessed in the present study. Although these gains may reflect motor learning, learning is generally distinguished from temporary changes in performance by its relative persistence and transfer to other performance conditions. Because the present study did not include retention or transfer tests, it cannot be determined whether the observed improvements would persist after the intervention was withdrawn or transfer to competitive match performance (Hodges & Williams, 2019). Future studies should therefore incorporate delayed retention tests and match-based transfer measures to establish whether the observed gains represent durable learning. The importance of such follow-up assessment is also reflected in intervention research in which delayed posttests are used specifically to examine whether immediate gains are maintained over time (Yıldırım & Turgut, 2025). The pattern of weekly scores presented in Figure 4 provides additional insight into the development of performance during the intervention. The experimental group continued to improve across the training period, whereas improvement in the control group became less pronounced from approximately the fifth week onward. Rather than demonstrating deliberate practice in a strict theoretical sense, this pattern suggests that the data analytics-based model may have supported more focused and continuously adjusted practice. By providing athletes with performance-specific information, the intervention enabled training to be directed toward aspects requiring further improvement. This interpretation is consistent with evidence showing that immediate and targeted feedback can help performers identify specific areas requiring improvement and make more focused adjustments during subsequent practice (Noor, 2026). Similarly, real-time feedback combined with progress tracking can facilitate the identification of strengths and weaknesses and support continuous performance adjustment (Dorji et al., 2026). In contrast, feedback that is insufficiently specific or timely may provide less guidance for targeted correction and subsequent performance improvement (Davor et al., 2026).

The 17.2% improvement observed in the control group also indicates that conventional coaching and repeated practice were associated with meaningful performance gains during the eight-week period. This improvement should be considered when interpreting the larger gains of the experimental group. Several mechanisms may have contributed to the control group's improvement, including increased familiarity with the AAHPERD test through repeated administration, continued exposure to regular coaching and practice, and possible maturation or general practice-related development over the intervention period. Because these mechanisms were not independently measured, however, they should be regarded as plausible explanations rather than established causes. Nevertheless, the experimental group improved by 45.6%, compared with 17.2% in the control group, representing a 28.4-percentage-point difference in relative improvement. Together with the between-group posttest findings, this pattern provides additional descriptive evidence that the data analytics-based coaching model offered benefits beyond those observed under conventional training alone.

4.3. The Role of Technology in the Intervention

The intervention involved a combination of three components – statistical performance analysis with Data Volley, biomechanical assessment with the use of CNN-LSTM system, and personalized feedback. These three components might have interacted synergistically to improve learning processes since statistical analysis gave the knowledge of results [KR] giving information on where the serve landed, accuracy in relation to target zones, and trends in serves, which is essential for skill learning as it gives athletes the ability to understand consequences of their actions and make adjustments (Magill & Anderson, 2017). Biomechanical assessment, in contrast, provided knowledge of performance [KP] by supplying information about movement characteristics such as arm angle, trunk rotation, contact point, and follow-through. This information enabled athletes to relate specific features of movement execution to observed performance outcomes. Personalized feedback then integrated KR and KP by translating these data into athlete-specific corrective priorities. Rather than requiring athletes to attend equally to multiple technical variables, this approach may have helped them concentrate on the movement components most in need of adjustment. Evidence from technology-supported learning similarly indicates that performance analysis combined with data-driven and personalized feedback can provide objective information about specific areas for improvement and support more targeted subsequent action (Davor et al., 2026; Fitriati & Williyan, 2025; Sökmen et al., 2026). Conceptually, this process resembles a formative assessment cycle in which performance data are collected, interpreted to identify areas requiring improvement, translated into instructional decisions and personalized feedback, followed by further practice and reassessment (Sukenti & Tambak, 2026). Technology supported this iterative process by facilitating standardized data collection, more immediate feedback, progress monitoring, and repeated opportunities for performance adjustment (Davor et al., 2026; Dorji et al., 2026). In sport-related contexts, video-supported approaches similarly allow coaches and athletes to record, review, and analyze specific aspects of movement performance, thereby supporting more systematic reflection and technical refinement (Özkara, 2025). Thus, the advantage of the present model may lie less in technology alone than in its capacity to support a structured cycle of performance measurement, diagnosis, individualized feedback, corrective practice, and reassessment.

Nevertheless, the present study cannot determine whether the observed effects resulted specifically from the technological tools or from other features embedded within the intervention, such as increased coaching attention, greater feedback specificity, more frequent performance monitoring, or their combination. Future research should therefore employ component-based dismantling or factorial designs that separate statistical analysis, biomechanical assessment, personalized feedback, and technology-assisted delivery. Such designs would make it possible to determine the unique contribution of each component and establish whether technology provides additional benefits beyond equally individualized and specific coaching delivered without technological support.

4.4. Consistency of Effects Across Positions and Time

Results of the exploratory analyses by positions (see Table 11) showed that the intervention was successful for all positions; the biggest changes were seen in open servers (9.20 points), while the smallest but statistically significant differences in middle blockers (8.00 points). Thus, one can say that the model did not favor any particular position. Middle blockers, whose service practice frequency is typically lower than in the case of servers and outside hitters, achieved statistically significant improvements. It aligns with findings of Silva et al. (2020), who argued that the use of data could give more benefits to athletes with smaller technical training volume since they would get more efficient feedback.

Nevertheless, subgroup analyses should be treated with a great deal of caution because of the low sample size (4-6 players per position per group). *p*-values (.001 –.008) should be taken for exploratory purposes; they are susceptible to Type I errors owing to multiple testing. There was no correction for multiple testing.

5. Implications

Through this study, the scientific domain of sports training science has been enriched by associating recent developments in analytical technology to their application in the context of coaching management. Previous studies concentrated more on technical aspects without any focus on the aspect of data management and decision making based on evidence (HakemZadeh & Rousseau, 2024). In this study, an overall framework has been developed, including three components: data collection, data analysis, and decision making regarding training.

This study has confirmed the theory of augmented feedback Schmidt and Lee (2023). according to which specific feedback that is provided in close proximity to performance is helpful for better acquisition of skills. The multimodal feedback (statistical, biomechanical, and personalized feedback) provided through the intervention has been designed to target more than one aspect of learning. Moreover, this study has confirmed the theory of deliberate practice (Van Mullem, 2016) where quality practice leads to better results compared to random repetition.

The outcomes suggest that volleyball coaching programs at the club and academy levels must take into account the use of a coaching methodology based on data analytics. In this regard, the FIVB Volleyball Empowerment project has created much impetus for this idea, but its implementation is complicated by lack of resources and coaches' capabilities. In this context, the present study shows the need for training and certification programs for coaches to be able to use analytical technologies like Data Volley and interpret biomechanical data generated by AI (Qi et al., 2024).

Nevertheless, making recommendations about general implementation is premature due to a number of factors, among which are small sample size (only 40 men from one region were involved), short-term intervention (8 weeks), absence of measurements for retention and match transfer, high expenses on technologies, impossibility to separate intervention effect from personalized feedback, and unproven technical system.

6. Limitations

There are a number of significant limitations of this study that need to be mentioned. First of all, due to the small sample size (N=40) of the study, its low statistical power and non-generalizability as only male athletes between 15 and 18 years old from one region of Indonesia were included. This means that the findings of the study can hardly be generalized to female athletes, adult athletes, younger athletes, and any other geographic settings. Second, the duration of the intervention (eight weeks) is too short in order to evaluate the long-term impact and the persistence of skills acquired by athletes during the intervention. Third, since the intervention was carried out in the form of three components bundle (statistical analysis, biomechanical assessment, and personalized feedback), the study could not identify the contribution of each component separately to the results achieved. Fourth, the experimental and control conditions of the intervention differed not only in the degree of feedback specificity and personalization but also in terms of technology used in the experimental group. Fifth, there might have been a coach effect on the results achieved since, despite the training of coaches in the intervention protocol, the enthusiasm, skills, and attention level of coaches could have been different for experimental and control conditions. Sixth, participants and coaches were not blinded to the condition they were in, even though the people assessing the results of the intervention were blinded, what could have affected their expectations and performance. Seventh, weekly measurements could have created a testing effect as participants became accustomed to the test procedure. Eighth, the subgroup analyses were conducted on the basis of multiple comparisons without adjustment for increased Type I error. Ninth, the study did not evaluate whether the skills acquired were successfully used in matches or persisted after the withdrawal of the intervention. Tenth, the high cost of implementing the intervention (subscribing to the Data Volley software, purchasing cameras, and providing the ability for using CNN-LSTM AI) is an obstacle for clubs with a tight budget. Eleventh, psychological variables such as motivation, self-confidence, and anxiety have not been evaluated.

7. Conclusion

From the results and discussion, the model of coaching based on data analytics proved to have a significant impact on the performance of the athletes regarding the improvement in the accuracy of serving in volleyball. There is a significant difference between the experimental and control groups with large effect size. However, the results can only be valid for the model and population considered in the experiment.

Future research must address the weaknesses in order to strengthen the results and make them more relevant. Among them there are larger sample sizes, dismantling studies, psychological factors, etc. As for practical application of the model, it should be conducted with great caution and consideration of the feasibility of its implementation, costs, and requirements for the coach.

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Data availability: The datasets generated and/or analyzed during the current study are not publicly available due to ethical and privacy considerations but are available from the corresponding author upon reasonable request.

Declaration of interest: The authors declare that they have no conflict of interest.

Ethics Declaration: All participants were student athletes, and informed consent was obtained from their legal guardians. Written informed consent was provided by a parent or guardian for each participant prior to their inclusion in the study. Participants were also informed of their right to withdraw from the study at any time without penalty**.**

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