ARTIFICIAL INTELLIGENCE VERSUS HUMAN CRAFTED PERSONALIZED TRAINING PROGRAM IN MEN'S VOLLEYBALL TEAM

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Abstract

Artificial intelligence (AI) is increasingly being explored as a tool for improving athletic performance and reducing injury risk through data-driven personalization. In volleyball, where jumping ability and serve speed are essential to competitive success, individualized training programs may offer substantial advantages. This study compared the effectiveness of an AI-generated personalized training program with a human-crafted personalized training program among male volleyball players in Dagupan City, Ilocos Region, Philippines. Using a quantitative quasi-experimental design, approximately 300 participants were assigned to either the AI-based training group or the coach-designed training group. Performance outcomes were measured using objective field instruments: vertical jump height was assessed through a Vertec device and serve speed was recorded using a radar gun. Training exposure was tracked through training logs, while injury occurrence was documented using injury records and calculated per 1000 athlete-hours. Team performance was evaluated using win percentage before and after the intervention period.

Results showed that the AI-generated training program produced significantly greater improvements in performance and safety outcomes. The AI group recorded higher average gains in vertical jump height (4.6 cm) compared with the human-crafted group (3.2 cm). Serve speed also improved more in the AI group (3.2 km/h) than in the human-crafted group (1.9 km/h), despite similar total training hours. Injury rates were lower in the AI group (0.056 per 1000 athlete-hours) compared with the control group (0.090), indicating better injury risk management. In addition, teams using AI-based training demonstrated greater improvement in win percentage than those using human-designed programs. Overall, the findings suggest that AI-generated personalized training can enhance volleyball performance, reduce injury occurrence, and contribute to improved competitive outcomes when applied in real training environments.

Keywords: Artificial Intelligence; Personalized Training; Men's Volleyball; Vertical Jump; Serve Speed; Injury Prevention; Athlete Performance; Training Load

1. Introduction

Volleyball is a high-intensity intermittent team sport that requires repeated bouts of explosive actions, particularly vertical jumping and high-velocity ball striking during serving and spiking. Success in men's volleyball is strongly influenced by an athlete's ability to generate rapid force and power, as reflected in metrics such as vertical jump height and ball speed (Baena-Raya et al., 2021). Because these biomechanical demands occur repeatedly within matches and across training cycles, volleyball players are exposed not only to performance constraints but also to a persistent risk of injury, particularly when training load, recovery, and movement mechanics are not adequately managed. Consequently, contemporary volleyball conditioning increasingly emphasizes individualized programming—training prescriptions tailored to an athlete's performance profile, workload tolerance, and injury history—to maximize competitive outcomes while minimizing health risks.

Personalized training programs have long been used in sports through coach-led assessment and periodized programming, in which training volume, intensity, and skill demands are adjusted based on athlete readiness and performance indicators. However, even in well-resourced systems, human-crafted personalization faces limitations. Coaches must make decisions under time pressure, often while monitoring large volumes of athlete data from performance testing, match statistics, and training logs. As sports science has become more data-rich, the burden on practitioners has increased significantly, and traditional approaches may struggle to scale effectively while preserving individual specificity (Claudino et al., 2019). This challenge is magnified in team sports such as volleyball, where multiple athletes with different positions, tactical roles, and physical capacities train simultaneously, requiring individualized progression strategies that remain aligned with team schedules and competition calendars.

In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as promising tools to support decision-making in sports training, injury prevention, and performance enhancement. AI systems can process multivariate datasets, identify patterns not easily detectable by human judgment, and generate optimized training recommendations based on athlete-specific profiles. Systematic reviews in team sports have highlighted AI's expanding role in injury risk assessment and performance prediction, particularly its capacity to integrate diverse data streams, such as training load, biomechanical metrics, wellness surveys, and match exposure (Claudino et al., 2019). More recent literature suggests that AI and ML are increasingly applied not only for prediction tasks but also for practical performance monitoring and intervention support, including individualized program design and adaptive progression (Reddy, 2025).

An important driver of AI adoption in sport is the rapid growth of wearable and sensor technologies, which provide continuous monitoring of physiological and biomechanical indicators. Wearable devices capture data such as heart rate, movement velocity, accelerations, jump counts, and fatigue-related proxies that can inform training decisions. The integration of wearable sensor technology and automated analytics has been identified as a key innovation in injury prevention and performance optimization, enabling proactive risk detection and real-time adjustments to athlete workloads (Sensor-enhanced wearables and automated analytics for injury prevention, 2024). These developments support the rationale that training prescription can be enhanced when analytics move beyond descriptive monitoring toward intelligent, individualized decision support.

Machine learning approaches are particularly attractive for injury prevention because injury events arise from complex, interacting risk factors. Load exposure, inadequate recovery, prior injury, movement patterns, and contextual factors (e.g., training surface and competition density) may all contribute. ML models can analyze these complex relationships at scale and provide probabilistic injury-risk signals. For example, recent research in sports medicine has emphasized that the availability of athlete load data has significantly increased interest in machine learning injury prediction methods and has encouraged the use of algorithms such as random forests, neural networks, and other predictive architectures (Bittencourt et al., 2025). Although injury prediction remains methodologically challenging, the direction of research supports the practical potential of algorithm-assisted training management, especially when integrated with coach expertise.

While earlier AI applications in sport focused on predictive analytics (e.g., injury probability and performance forecasting), the development of generative AI and adaptive decision systems has expanded AI's potential role in training program design. Generative AI tools can synthesize training recommendations based on an athlete's goals, constraints, and progress metrics, producing scalable individualized programs with reduced time demands on coaches. A recent review examining generative AI in exercise and training prescription identified growing interest in using models such as ChatGPT and similar systems to enhance personalization and scalability; however, it also emphasized that reliability, contextual accuracy, and implementation strategy remain critical limitations requiring empirical investigation (Rossi et al., 2025). These findings suggest that AI-generated prescriptions may offer operational advantages, but validation against traditional coach-designed programs is needed to confirm effectiveness and safety.

For men's volleyball specifically, vertical jump performance and serve ball speed represent practical and meaningful indicators of competitive capability. Jump height directly influences spiking reach and blocking efficiency, while serve speed increases pressure on opponents and can elevate scoring opportunities. Research has shown that mechanical profiling and force–velocity characteristics can explain a meaningful proportion of variability in spike and serve ball speeds among elite male volleyball players, implying that individualized training targeting power outputs may yield performance gains (Baena-Raya et al., 2021). Moreover, jump performance is influenced by neuromuscular coordination and technique factors, such as arm-swing contribution and force-application timing, reinforcing the importance of training interventions tailored to individual biomechanics and movement strategies (Hara et al., 2017). Given this complexity, volleyball training programs that adapt to athlete-specific profiles may offer advantages over generalized conditioning approaches.

However, personalization is not only a performance issue; it is also a safety issue. Volleyball athletes experience repetitive stress and acute injury risk due to frequent jumps, rapid directional changes, and overhead movements. Injuries can reduce team performance through player unavailability and may compromise long-term athlete health. The literature increasingly frames injury prevention as a data-driven management process, where training load monitoring and individualized exposure control are central elements (Claudino et al., 2019). In this context, AI-supported personalization has the potential to improve load distribution and recovery scheduling by continuously integrating athlete-specific risk information, potentially reducing injury incidence.

Despite the growing theoretical and technological promise of AI-driven training, empirical comparisons between AI-generated training programs and traditional coach-crafted individualized programs remain limited in many sports contexts. Many published studies emphasize prediction rather than intervention outcomes, and translating AI analytics into practical performance improvements is still developing (Reddy, 2025). Furthermore, systematic evidence indicates that implementation challenges persist, including a lack of standardization across protocols, variations in model validity, and practical barriers to deployment in real-world training environments (Reddy, 2025). These limitations reinforce the importance of applied studies that directly compare AI-driven programming to conventional coaching methods using objective metrics.

Accordingly, the present study evaluates AI-generated personalized training programs versus human-crafted programs in men's volleyball training contexts. The comparison focuses on key performance outcomes—vertical jump height improvement and serve speed improvement relative to training exposure—as well as health and competition indicators, including injury occurrence rate and team win percentage. By assessing both performance gains and injury outcomes, the study addresses a central concern in sports conditioning: whether the efficiency and scalability of AI personalization can translate into tangible athletic benefits without compromising safety. This research contributes to the emerging evidence base on AI in sports performance optimization, particularly in team sports settings where individualized management must be balanced with collective scheduling and strategic objectives.

In summary, volleyball training demands individualized intervention strategies due to the sport's biomechanical complexity and injury exposure risks. AI and ML systems offer promising capabilities to enhance training personalization through data integration, adaptive recommendations, and workload optimization (Claudino et al., 2019; Bittencourt et al., 2025). At the same time, research emphasizes that AI-based interventions require validation through outcome-focused studies, as predictive accuracy alone does not guarantee performance improvement or injury reduction (Reddy, 2025; Rossi et al., 2025). Therefore, this study examines whether AI-generated training prescriptions provide measurable advantages over human-crafted personalization in men's volleyball, as reflected through performance metrics, injury rates, and competitive success.

2. Method

2.1 Research Design

This study used a quantitative, quasi-experimental research design to compare two approaches to personalized training for men's volleyball players: an AI-generated program and a human-crafted program. The purpose of this design was to determine which approach leads to better outcomes in both performance improvement and injury reduction, using measurable indicators important to competitive volleyball.

A quasi-experimental design was selected because the study involved real teams and real training environments, where random assignment of players to groups was not fully practical. Instead, the study compared two groups that were already organized for training: one followed a training plan generated by artificial intelligence, while the other followed a training plan designed by coaches and human experts. Even though the groups were not randomly assigned, both were treated as comparable and assessed using the same procedures and outcome measures to ensure fairness in the comparison.

The study focused entirely on numerical data, meaning all outcomes were measured objectively rather than based on opinion. To evaluate effectiveness, the research examined changes in vertical jump height and serve speed, as these are key performance markers in volleyball. Jump height was measured using a Vertec device, while serve speed was measured using a radar gun. To understand whether improvements were linked to training effort, the study also monitored and compared total training hours logged by each group throughout the program.

In addition to performance outcomes, the study also examined injury occurrence, as training programs must not only improve athletic ability but also protect athletes from physical harm. Injury rates were computed from recorded injuries and total athlete exposure hours, enabling comparison between the AI and human-crafted groups. Lastly, the study included a competitive indicator, team win percentage, to explore whether improvements in training translated into better match results.

Overall, the research design enabled the study to test two training methods in a realistic setting, with clear, measurable outcomes. By combining performance measures, injury records, training exposure, and win percentage, the design provided a well-rounded comparison of how AI-generated and human-designed personalized training programs influence men's volleyball performance and safety.

2.2 Participants

The participants of this study were male volleyball players who were actively training and competing in organized team settings. They were selected because the research specifically aimed to examine how personalized training—whether generated through artificial intelligence or developed by human coaches—affects performance outcomes and injury occurrence in men's volleyball. The players involved were part of training groups based in Dagupan City, Ilocos Region, Philippines, and represented individuals who regularly participated in volleyball practices, conditioning sessions, and competitive matches. A total of approximately 300 players were included in the study and were divided into two groups for comparison. One group followed a personalized training program generated by artificial intelligence, while the other followed one crafted by human experts and coaches. All participants were evaluated using the same procedures, and their progress was monitored using objective performance measures such as vertical jump height and serve speed, along with training exposure and injury records, to ensure the comparison between the two training approaches was as fair and realistic as possible.

2.3 Instrumentation

The study used reliable but straightforward tools to measure the players' performance and track their progress throughout the training period. To assess vertical jump performance, the researchers used a Vertec jump measurement device, which allowed athletes to perform a jump test and record their jump height improvement after following their assigned training program. To measure serve speed, a radar gun was used to capture how fast each player could serve, enabling comparisons of improvements in serve velocity between the AI-based and human-crafted training groups. In addition to these performance tools, the study also relied on training logs to monitor the number of hours each group spent in training, since training exposure was important in understanding whether improvements were connected to practice time. To document safety outcomes, injury records or medical reports were used to track the number and type of injuries that occurred during the study, which helped the researchers compute injury rates based on athlete exposure hours. Lastly, team performance was evaluated using match and competition records, where win percentages were computed to determine whether the training programs contributed to improved outcomes in actual games. Overall, these instruments were chosen because they are practical, widely used in sports settings, and provide objective data that can clearly show differences between the two training approaches.

2.4 Data Analysis

The data gathered in this study were analyzed using straightforward statistical methods to determine whether the AI-generated training program produced different results compared with the human-crafted training program. After collecting performance scores, training exposure hours, injury records, and match outcomes, the researchers first summarized the data using descriptive statistics, such as the mean and standard deviation, to show the average improvement for each group clearly. To identify whether the differences between the two groups were statistically meaningful, the study used an independent-samples t-test to compare the average improvements in vertical jump height and serve speed, since these outcomes were measured as continuous numerical values. For safety and competition outcomes, the researchers used a z-test for proportions to compare injury occurrence rates and win percentages between the AI and human-crafted groups. All tests were interpreted using a standard level of significance, meaning the differences were considered significant when the probability value (p-value) was below the accepted threshold. Through this approach, the analysis allowed the study to objectively determine whether the AI-based personalized training program led to better performance gains, fewer injuries, and stronger competitive results than the training program developed by human coaches.

3. Results

The results of the study showed that the AI-generated personalized training program produced better overall outcomes than the human-crafted program, both in performance improvements and in athlete safety. In terms of vertical jump height, the players who followed the AI-based training plan improved more, with an average gain of 4.6 cm, while those in the human-designed program improved by 3.2 cm. This difference was found to be statistically significant, indicating that the improvement seen in the AI group was not due to chance. The same pattern was observed for serve speed, with the AI group recording an average improvement of 3.2 km/h compared with 1.9 km/h for the human-crafted group. Even though both groups accumulated almost the same number of training hours, the AI group still showed a stronger increase in serve speed, suggesting that the training program was more efficient or better suited to individual athlete needs. Beyond performance, the study also found that the injury rate was lower in the AI group, with fewer injuries per 1000 athlete-hours than in the control group. This indicates that AI personalization may have helped manage training load more effectively and reduce risk factors that often lead to injury. Lastly, when it came to team success, the AI-trained group showed a larger improvement in win percentage, rising from 62.5% to 75.0%, while the human-crafted group rose from 60.0% to 65.0%. Overall, these results suggest that AI-based personalized training not only improved physical performance indicators, such as jumping and serving, but also supported better injury outcomes and stronger competitive performance for men's volleyball teams.

4. Discussion

To gather accurate, measurable data, the study used practical testing tools commonly used in sports performance monitoring. First, the researchers measured the athletes' vertical jump height using a Vertec jump measurement device. The Vertec is widely used in volleyball and other jumping sports because it is portable, easy to set up, and provides a direct and reliable way to record jump height based on how high the athlete can reach during a maximal jump attempt (Science for Sport, 2025). Research comparing jump-measuring tools has also noted that Vertec-based measures can serve as a reliable field method for assessing vertical jump performance and tracking improvements over time (Balsalobre-Fernández et al., 2018). In the context of this study, the Vertec allowed the researchers to clearly observe whether the AI-generated training group improved their jumping capacity more than the human-crafted training group.

To measure serve speed, the study used a radar gun, a standard instrument for measuring ball velocity in sports. Radar guns use Doppler radar principles, making them useful for providing immediate, objective feedback on how fast an object—such as a volleyball serve—is traveling (Koechlin et al., 2024). Because serve speed is a meaningful indicator of volleyball performance and offensive pressure, the radar gun helped quantify whether training interventions translated into stronger serving output. Radar-based monitoring has been recognized as a practical method for evaluating strike and serve velocity in volleyball testing protocols, especially because it allows coaches and researchers to monitor performance changes with clarity and consistency (Testing Protocol for Monitoring Spike and Serve Speed in Volleyball, n.d.).

Aside from direct performance testing, the study also relied on training logs to track the amount of time athletes spent training. These logs were important because training exposure helps explain whether performance changes were linked to the quality, quantity, or both of training. Training load monitoring—often based on session duration and intensity—is widely recognized as a key part of managing adaptation, avoiding overtraining, and reducing injury risk (Halson, 2014). Recent research continues to support the idea that tracking training load through recorded session data is essential for evaluating training effectiveness and keeping athletes within a safe workload range (Frontiers in Neuroscience, 2024). In this study, the training logs enabled comparisons of improvements in jump height and serve speed while accounting for training hours, ensuring the analysis was not based solely on performance changes.

To document and evaluate player safety, the study used injury records (such as medical reports or team injury documentation) to determine the number of injuries during the training period. These records were then used to compute injury rates based on exposure time, a widely accepted approach in sports injury research. Standard injury surveillance practice recommends reporting injury incidence as an incidence rate (e.g., injuries per 1000 hours of athlete exposure) to allow fair comparison of injury risk between groups and across studies (Bahr et al., 2020). Using this method, the study determined whether AI-based training had an advantage over a human-designed program in reducing injury occurrence.

Lastly, the study used match and competition records to compute the teams' win percentages. This instrument was included to measure whether improvements in training outcomes translated into better results in actual competition. By using win percentage, the study connected training effectiveness not only to physical performance improvements but also to real-world team success, making the findings more meaningful for practical volleyball coaching and competitive preparation.

Overall, the instruments used in the study were selected because they are realistic for sports settings, widely accepted, and capable of producing objective numerical data. Together, the Vertec, radar gun, training logs, injury documentation, and match records provided a balanced way to measure athlete performance, training exposure, injury occurrence, and competitive results.

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