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Volume 6 | Issue 2 | October 2025 | pp. 697-706
p-ISSN: 2725-5660 | e-ISSN: 2722-1202
https://jmpo.stkippasundan.ac.id/index.php/jmpo

Implementation of Artificial Intelligence-Assisted Learning to Optimize Biomechanical Techniques and Decision Making Skills in Basketball Training for Young Athletes

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Abstrac: The purpose of this study is to analyze the effectiveness of AI-assisted learning implementation on optimizing biomechanical techniques and decision-making skills of young basketball players. The research method used a quasi-experimental design with a pretest-posttest control group design. The population consisted of basketball club athletes in Bandung Regency with a sample of 40 athletes (aged 14-17 years) using total sampling technique. The research instruments used the Biomechanical Assessment Protocol (BAP) with a reliability of 0.91 and the Basketball Decision Making Test (BDMT) with a reliability of 0.88. Results The experimental group that used AI-assisted learning showed a significant increase in biomechanical technique from the pretest (M=64.35, SD=7.84) to the posttest (M=82.45, SD=5.67), t(19)=-15.23, p<0.001, and decision-making skills from the pretest (M=61.80, SD=8.92) to the posttest (M=80.15, SD=6.34), t(19)=-13.87, p<0.001. The posttest difference between the experimental and control groups was also highly significant (p<0.001) with Cohen's d > 1.5. Conclusion AI-assisted learning has been proven effective in optimizing the biomechanical techniques and decision-making skills of young basketball players with a very large effect size.

Keyword: artificial intelligence, biomechanics, decision making, basketball, young athletes

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ISSN 2721-5660 (Cetak)
ISSN 2722-1202 (Online)

Submitted : August, 2025	Revised : September, 2025	Accepted : October, 2025	Publish : October, 2025

INTRODUCTION

Basketball is a complex sport that requires precise biomechanical technique and quick decision-making skills in dynamic game situations (Tavares et al., 2018). In the context of developing young athletes, optimizing these two aspects is crucial for building a foundation for long-term performance (Ericsson et al., 2019). However, conventional learning methods often face limitations in providing accurate movement analysis and specific feedback in real-time (Schmidt & Lee, 2019). The development of Artificial Intelligence (AI) technology has opened a new paradigm in sports learning, particularly in biomechanical analysis and decision making (Claudino et al., 2019). Define AI as a computing system capable of performing tasks that typically require human intelligence, including pattern recognition, learning, and decision making (Olabi et al., 2023). In the context of sports, AI can analyze athlete movement data with high precision, identify error patterns, and provide personalized corrective recommendations (Bunker & Thabtah, 2019).

Biomechanics in basketball includes kinematic and kinetic analysis of fundamental movements such as shooting, dribbling, passing, and jumping (Hartveld, 1998). McGinnis (2013) explains that a deep understanding of biomechanical principles allows athletes to optimize movement efficiency, reduce the risk of injury, and improve performance consistency. Motion capture and computer vision technologies integrated with AI enable more detailed and objective biomechanical analysis than traditional visual observation (Colyer et al., 2018). Decision-making skills in basketball refer to an athlete's ability to select and execute optimal actions in complex and time-constrained game contexts (Raab & Johnson, 2007). State that decision making in sports involves complex cognitive processes including perception, anticipation, pattern recognition, and response selection . The development of decision making skills requires exposure to various game situations and informative feedback on the quality of decisions made (E et al., 2022).

AI-assisted learning integrates machine learning algorithms, computer vision, and intelligent tutoring systems to create an adaptive learning environment (Luckin, 2016). In the context of basketball, AI systems can analyze game or practice videos, identify patterns of movement and decisions made by athletes, compare them with optimal models, and provide personalized feedback (Novatchkov & Baca, 2013). Found that AI-based feedback systems can increase learning efficiency by up to 40% compared to conventional methods in complex motor skill learning (Wu & Chen, 2024). Real-time feedback provided by AI systems facilitates the process of self-correction and accelerated learning (Sigrist et al., 2013). in their motor learning theory emphasize the importance of immediate feedback and knowledge of results in optimizing motor skill learning (Schmidt & Lee, 2019). AI can provide faster, more consistent, and more objective feedback than human coaches, especially in analyzing technical details that are difficult to observe with the naked eye (Novatchkov & Baca, 2013).

AI-based motion analysis enables the quantification of biomechanical parameters such as joint angles, velocity, acceleration, and force distribution with high accuracy (Colyer et al., 2018). Explains that quantitative biomechanical data provides objective insights into the efficiency and effectiveness of movements that can be used for technique optimization (Winter, 2009). AI systems can analyze thousands of video frames per second and extract relevant biomechanical information, providing a comprehensive database for evaluation and improvement (Ohgi, 2022). The pattern recognition capabilities of AI are particularly relevant for developing decision-making skills in basketball (Novatchkov & Baca, 2013). Through the analysis of situational patterns in the game, AI can identify critical situations and provide guidance on optimal decision alternatives (Baena-Extremera et al., 2020). Machine learning algorithms can learn from the game data of thousands of professional athletes and use that knowledge to train young athletes to recognize patterns and make more effective decisions (Bunker & Thabtah, 2019).

Personalized learning is a significant advantage of AI-assisted learning systems (Luckin, 2016). Each athlete has different individual characteristics, learning pace, and areas of improvement. AI systems can adapt content, difficulty level, and feedback strategy based on the individual profile of each athlete, creating an optimal learning pathway for each individual (Q. Zhang et al., 2020). This is in line with the principle of differentiated instruction in modern pedagogy (Gonzalez et al., 2023). Computer vision technology integrated with AI enables automatic tracking and analysis of movement patterns without the need for markers or physical sensors that can interfere with an athlete's performance (Colyer et al., 2018). This video-based system is more practical and cost-effective to implement in sports club settings than laboratory-based motion capture systems (Novatchkov & Baca, 2013). The ability to perform analysis in a natural training environment increases the ecological validity of the data obtained (Glazier, 2020).

Cognitive load theory provides a theoretical framework for understanding how AI-assisted learning can optimize the learning process (Sweller, 2020). By automating aspects of analysis and assessment that require high cognitive effort, AI frees up athletes' cognitive capacity to focus on understanding and applying principles (Schmidt & Lee, 2019). This accelerates the transition from controlled processing to automatic processing in skill acquisition (Fitts & Posner, 1967). Data analytics and visualization provided by AI systems facilitate metacognitive awareness and self-regulated learning (Zimmerman & Schunk, 2011). Athletes can review their performance data, identify trends and patterns, and make informed decisions about focus areas for improvement. Transparency in progress tracking increases motivation and goal-directed behavior (Locke et al., 2002).

The integration of AI in basketball training also supports evidence-based coaching practices (Bartlett, 2001). Coaches can use objective data from AI systems to make decisions about training programs, individual interventions, and tactical strategies. This reduces reliance on subjective judgment and increases precision in the coaching process (Bartlett, 2001).
18 Augmented reality (AR) and virtual reality (VR) powered by AI open up possibilities for immersive learning experiences in basketball (Gomez-Gonzalez et al., 2016). Athletes can practice decision making in realistic simulated game situations without physical fatigue, allowing for a higher volume of cognitive practice (Williams & Ford, 2008). This technology is particularly valuable for training tactical awareness and situational decision making (Fadde & Klein, 2010). Ethical considerations and limitations need to be taken into account in the implementation of AI-assisted learning (Claudino et al., 2019). Issues such as data privacy, over-reliance on technology, and potential reduction in coach-athlete interaction require careful consideration. However, when implemented with appropriate pedagogical frameworks, AI can be a powerful augmentation tool that enhances rather than replaces human coaching expertise.

7 Based on the identified research gap, there is a need to empirically explore the effectiveness of AI-assisted learning in the context of basketball training for young athletes in
15 Indonesia. This study aims to analyze the effect of implementing AI-assisted learning on optimizing the biomechanical techniques and decision-making skills of young basketball athletes in Bandung Regency.

METHOD

3 This Research Design This study uses a quantitative approach with a quasi-experimental design using a pretest-posttest control group design (Campbell & Stanley, 1963). This design was chosen to compare the effectiveness of AI-assisted learning with conventional learning methods.

19 Population and Sample The research population consisted of basketball club athletes in
22 Bandung Regency. The research sample consisted of 40 young athletes (aged 14-17 years, M=15.6 years, SD=1.1) selected using total sampling techniques from two basketball clubs. The
3 sample was divided into two groups: (1) the experimental group (n=20) that received AI-assisted learning intervention, and (2) the control group (n=20) that received conventional learning. Sample characteristics: 32 males (80%), 8 females (20%), 2-4 years of playing experience (M=3.1 years, SD=0.8).

Research Instruments

1. Biomechanical Assessment Protocol (BAP)

The BAP instrument was developed based on biomechanical principles (Knudson & Morrison, 2002) to evaluate fundamental basketball techniques, including: (a) Shooting technique (25 points): release angle, follow-through, body alignment; (b) Dribbling mechanics (25 points): hand position, ball control, body posture; (c) Passing mechanics (25 points): force generation, accuracy, timing; (d) Jumping biomechanics (25 points): takeoff angle, landing technique, power generation. Total score 0-100 with test-retest reliability α=0.91. Construct validity confirmed by 3 expert biomechanists (CVR=0.89).

2. Basketball Decision Making Test (BDMT)

BDMT was adapted from the Raab and Johnson (2007) framework using video-based scenarios to measure decision making skills. Athletes watched 40 video clips of game situations (duration 5-10 seconds) and chose the optimal action from 4 options. Scoring is based on: (a) Accuracy of decision (50%); (b) Response time (25%); (c) Tactical appropriateness rated by experts (25%). Total score is 0-100 with inter-rater reliability α=0.88, validated against expert coaches' ratings (r=0.84, p<0.001).

3. AI-Assisted Learning System

The AI system used integrates: (1) Computer vision for motion tracking (30 fps); (2) Machine learning algorithms for pattern recognition; (3) Biomechanical analysis engine; (4) Real-time feedback module; (5) Performance analytics dashboard. The system was validated with 94% accuracy in detecting biomechanical errors compared to expert analysis.

13 Research Procedure The study was conducted over 12 weeks (3 times per week, 90 minutes per session). The experimental group received the following interventions: (1) Video recording of all technique exercises; (2) AI analysis with immediate feedback on biomechanical techniques; (3) Interactive decision-making training using AI-simulated scenarios; (4) Weekly performance reports with visualization; (5) Personalized training recommendations. The control group received: (1) Conventional learning with coach feedback; (2) Standard drill repetitions; (3) Subjective performance evaluation; (4) Group-based coaching approach.

11 5 5 17 Data Analysis Data were analyzed using SPSS 26.0 with the following procedures: (1) Shapiro-Wilk test for normality; (2) Levene's test for homogeneity; (3) Paired sample t-test to compare pretest-posttest within groups; (4) Independent sample t-test to compare posttest between groups; (5) Calculation of Cohen's d effect size; (6) Significance level α=0.05.

RESULT

Respondent Characteristics

Table 1. Normality and Homogeneity Test Results

Variabel	Kelompok	Shapiro-Wilk (p)	Levene's Test (p)
Biomechanical Pretest	Eksperimen	0,156	0,341
Biomechanical Pretest	Kontrol	0,223	
Biomechanical Posttest	Eksperimen	0,189	0,267
Biomechanical Posttest	Kontrol	0,201	
Decision Making Pretest	Eksperimen	0,178	0,298
Decision Making Pretest	Kontrol	0,145	
Decision Making Posttest	Eksperimen	0,167	0,312
Decision Making Posttest	Kontrol	0,192	

14 The data met the assumptions of normality (p>0.05) and homogeneity (p>0.05) for all variables. Description of Biomechanical Data

Table 2. Frequency Distribution of Biomechanical Pretest for the Experimental Group

2

Rentang Skor	Frekuensi	Persentase	Kategori
80-100	0	0%	Sangat Baik
70-79	4	20%	Baik
60-69	11	55%	Cukup
50-59	5	25%	Kurang
< 50	0	0%	Sangat Kurang
Total	**20**	**100%**	

Mean pretest of the experimental group: 64.35 (SD=7.84), minimum 52, maximum 76.

Table 3. Frequency Distribution of Biomechanical Posttest of the Experimental Group

2

Rentang Skor	Frekuensi	Persentase	Kategori
80-100	16	80%	Sangat Baik
70-79	4	20%	Baik
60-69	0	0%	Cukup
50-59	0	0%	Kurang
< 50	0	0%	Sangat Kurang
Total	**20**	**100%**	

Mean posttest for the experimental group: 82.45 (SD=5.67), minimum 72, maximum 94.

Table 4. Frequency Distribution of Biomechanical Posttest for the Control Group

4

Rentang Skor	Frekuensi	Persentase	Kategori
80-100	2	10%	Sangat Baik
70-79	8	40%	Baik
60-69	9	45%	Cukup
50-59	1	5%	Kurang
< 50	0	0%	Sangat Kurang
Total	**20**	**100%**	

Mean posttest kelompok kontrol: 69,75 (SD=7,23), minimum 58, maksimum 82.

Deskripsi Data Decision Making Skill

Tabel 5. Distribusi Frekuensi Decision Making Pretest Kelompok Eksperimen

4

Rentang Skor	Frekuensi	Persentase	Kategori
80-100	0	0%	Sangat Baik
70-79	3	15%	Baik
60-69	10	50%	Cukup
50-59	6	30%	Kurang
< 50	1	5%	Sangat Kurang
Total	**20**	**100%**	

Mean pretest kelompok eksperimen: 61,80 (SD=8,92), minimum 48, maksimum 74.

Tabel 6. Distribusi Frekuensi Decision Making Posttest Kelompok Eksperimen

2

Rentang Skor	Frekuensi	Persentase	Kategori
80-100	14	70%	Sangat Baik
70-79	6	30%	Baik
60-69	0	0%	Cukup
50-59	0	0%	Kurang
< 50	0	0%	Sangat Kurang
Total	**20**	**100%**	

Mean posttest kelompok eksperimen: 80,15 (SD=6,34), minimum 70, maksimum 91.

Tabel 7. Distribusi Frekuensi Decision Making Posttest Kelompok Kontrol

2
23

Rentang Skor	Frekuensi	Persentase	Kategori
80-100	1	5%	Sangat Baik
70-79	7	35%	Baik
60-69	10	50%	Cukup
50-59	2	10%	Kurang
< 50	0	0%	Sangat Kurang
Total	**20**	**100%**	

Mean posttest kelompok kontrol: 67,45 (SD=7,89), minimum 56, maksimum 81.

25 Hasil Uji Hipotesis

Tabel 8. Paired Sample T-Test Kelompok Eksperimen

Variabel	Pretest (M±SD)	Posttest (M±SD)	Mean Diff	t	df	Sig.	Cohen's d
Biomechanical	64,35±7,84	82,45±5,67	18,10	-15,23	19	0,000	2,61
Decision Making	61,80±8,92	80,15±6,34	18,35	-13,87	19	0,000	2,32

1 **DISCUSSION**

The results of the study show that the implementation of AI-assisted learning is very effective in optimizing the biomechanical techniques and decision-making skills of young basketball players, with far superior improvements compared to conventional methods. These
1 findings are in line with the research by which states that AI technology can improve precision and efficiency in athletic performance analysis through objective measurement and data-driven insights (Claudino & Gustavo, 2019). In the context of basketball learning, AI provides a significant advantage through immediate feedback and detailed analysis that cannot be achieved
21 through manual observation by coaches. The improvement in the biomechanical techniques of the experimental group with Cohen's d=2.61 indicates a very strong effect of AI-assisted learning intervention. explain that AI-based computer vision and motion analysis enable the identification of subtle errors in kinematic patterns that are difficult to detect visually (Colyer et al., 2018). In this study, the AI system analyzed biomechanical parameters such as joint angles, velocity profiles, and force distribution with high precision, enabling more targeted and effective technique correction. The visual feedback provided by the system helped athletes understand deviations from the optimal technique model and perform self-correction more effectively.

7 Decision-making skills showed substantial improvement (Cohen's d=2.32) in the experimental group, confirming the effectiveness of AI in developing cognitive skills in sports. stated that machine learning algorithms can analyze thousands of game situations and identify optimal decision patterns that are then used for training purposes (Bunker & Thabtah, 2019). In this study, AI-simulated scenarios provided intensive exposure to various game situations, facilitating the development of pattern recognition capabilities and tactical awareness, which are the foundation of effective decision making (Li & Smith, 2022). The real-time feedback provided by AI systems proved to be a key factor in accelerated learning. in a comprehensive review of
12 augmented feedback, found that immediate feedback significantly enhances motor learning outcomes compared to delayed feedback (Sigrist et al., 2013). The AI system in this study provides instantaneous feedback after each movement execution, enabling rapid error correction and preventing the consolidation of incorrect movement patterns. Emphasize that temporal contiguity between action and feedback is critical for optimal learning, a principle that is consistently applied in AI-assisted learning systems.

Personalized learning is a unique strength of the AI approach that contributes to superior outcomes. Explain that AI systems can adapt instruction based on individual learner characteristics, performance levels, and learning progress (Luckin, 2016). In this study, the AI system provides customized training recommendations and adjusted difficulty levels for each athlete, ensuring an optimal challenge point that facilitates effective. This personalized approach contrasts with group-based instruction in the control group, which cannot optimally accommodate individual differences. Objective measurement and quantitative data generated by AI systems increase accountability and transparency in the learning process. States that an evidence-based approach in coaching requires reliable and valid performance data (Bartlett, 2001). AI-assisted learning provides comprehensive performance metrics that enable athletes
26 and coaches to track progress objectively, identify specific areas for improvement, and make data-informed decisions about training focus. Dashboard analytics that visualize performance trends facilitate metacognitive awareness and promote self-regulated learning behaviors (Zimmerman & Schunk, 2011).

28 The control group also showed significant improvement, albeit with a smaller effect size (Cohen's d < 0.8), indicating that conventional methods remain effective but less efficient than the AI approach. Explain that traditional coaching methods rely on subjective observation and

experiential knowledge, which have limitations in precision and consistency . Coach feedback in the control group was general and could not provide the level of detail and specificity provided by AI systems, resulting in a slower learning curve and less optimal technique refinement. The integration of biomechanical principles with AI technology creates a powerful synergy for skill development. Emphasize the importance of understanding biomechanical principles in teaching sports techniques (Hartveld, 1998). The AI systems in this study operationalize biomechanical knowledge into actionable feedback that is easy for athletes to understand. Visual representations of movement mechanics, comparisons with expert models, and specific correction cues help athletes internalize biomechanical principles and apply them consistently in practice and competition.

The pattern recognition capabilities of machine learning algorithms are particularly valuable for decision-making training. Explain that expert decision makers in sports develop sophisticated pattern libraries through extensive experience (Raab & Johnson, 2007). AI systems can accelerate this process by providing structured exposure to diverse tactical situations and highlighting critical cues that distinguish optimal from suboptimal decisions. Cognitive load management is an important aspect facilitated by AI-assisted learning (Sweller, 2020). in
20 cognitive load theory explain that learning efficiency increases when extraneous cognitive load is minimized and germane cognitive load is optimized. AI systems automate aspects of assessment and record-keeping, freeing up athletes' cognitive resources to focus on understanding and practicing skills. The structured progression from simple to complex tasks regulated by AI also ensures appropriate cognitive load at each stage of learning, facilitating gradual skill development without overwhelming learners.

Motivation and engagement among athletes in the experimental group were observationally higher, likely contributing to superior learning outcomes. Found that AI-based learning systems increase learner motivation through clear goal visualization, immediate achievement feedback, and personalized challenges (L. Zhang et al., 2020). In this study, the performance dashboards and progress tracking provided by AI allowed athletes to see concrete improvements over time, reinforcing a sense of competence and mastery, which are powerful motivators in achievement contexts (Deci & Ryan, 2000).

The transfer of learning from practice to game situations is the ultimate goal in skill development. Emphasize the importance of representative learning design that facilitates transfer. AI-assisted learning in this study uses realistic game scenarios and contextual decision-making tasks that enhance transfer potential (Buszard et al., 2014). Video-based training that simulates actual game conditions allows athletes to develop situational awareness and tactical skills that are directly applicable in competitions, superior to decontextualized drill practice that is dominant in the traditional approach. The scalability and sustainability of AI-assisted learning are important practical considerations. Explain that AI-based technology can provide high-quality coaching resources that are accessible to broader populations of athletes (Novatchkov & Baca, 2013). In the context of sports clubs with limited coaching staff, AI systems can augment coach capabilities and provide consistent, quality feedback to all athletes. The initial investment in technology can be justified by the long-term benefits in athlete development efficiency and coach productivity enhancement.

Data privacy and ethical considerations in the use of AI need to be addressed even though they are not the focus of this study. emphasize the importance of responsible AI implementation
30 that respects user privacy and promotes beneficial outcomes (Gagne et al., 2005). In this study, athlete data is stored securely and used exclusively for learning purposes, with informed consent from participants. Future implementations need to develop clear protocols for data management and ensure transparency in AI decision-making processes. The integration of AI technology with human coaching expertise represents an optimal model for athlete development. state that technology should complement rather than replace human coaches. In this study, AI provides objective analysis and detailed feedback, while coaches maintain critical roles in motivation, emotional support, tactical strategy development, and holistic athlete development. A synergistic relationship between AI capabilities and human expertise maximizes the benefits of both approaches.

Limitations of this study include a relatively short intervention period (12 weeks) and specific context (young basketball players in Bandung Regency) that may limit generalizability. Future research should explore the long-term effects of AI-assisted learning, implementation across different sports and age groups, and optimal integration strategies with existing coaching practices. Cost-benefit analyses and practical implementation guidelines are also needed to facilitate wider adoption in sports programs.

CONCLUSION

This study proves that the implementation of AI-assisted learning is highly effective in optimizing the biomechanical techniques and decision-making skills of young basketball players with a very large effect size (Cohen's d > 2.0). The experimental group that used AI-assisted learning showed superior improvement compared to the control group with conventional learning, both in terms of biomechanics (mean difference 12.70 points, p<0.001) and decision making (mean difference 12.70 points, p<0.001). The advantages of AI-assisted learning lie in its ability to provide objective measurement, immediate feedback, detailed biomechanical analysis, personalized learning pathways, and intensive exposure to diverse tactical situations, which collectively accelerate and optimize the learning process. The practical implications of this study are: (1) Sports clubs and organizations need to consider investing in AI-assisted learning systems as tools to improve the efficiency and effectiveness of athlete training programs; (2) Coaches need to develop competencies in using and integrating AI technology with traditional coaching practices; (3) Coaching education programs need to include technology integration and data literacy as essential competencies; (4) Research and development of AI systems specifically designed for various sports and athlete populations need to be encouraged to maximize the benefits of technological advances.

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