Basketball Players' AI-powered Biomechanics Apps Improve Basketball Players' Shooting

Abstract

The deep integration of artificial intelligence (AI) into sports biomechanics has opened new prospects for improving athletic performance, especially in skill-based areas such as basketball shooting. This proposed study investigates the magnitude of improvement in the shooting accuracy of basketball players beyond 4.5 meters achieved by an AI-powered biomechanics application, HomeCourt, during a formal 35-day training period. By dividing 9 participants into five categories, AI-assisted training, coaching, and video-based training with no feedback are selected for experienced players, whereas for beginner-level players, only AI-assisted coaching-based training is chosen. All athletes perform three standardised shooting tests (Day 1, Day 28, and Day 35), comprising a total of 120 shots from six court locations. Shooting percentages and biomechanical measures such as release angle and leg angle are examined using raw performance data and AI feedback from HomeCourt. The results indicate that AI biomechanics apps may not significantly increase shooting accuracy over 35 days for experienced athletes when they adopt the app; however, there are significant changes in shooting mechanics and expedited benefits for beginners. Therefore, the scope of this study suggests it could serve as a complementary tool for basketball training, offering clear advantages for beginners in technique optimization and skill acquisition.

Keywords: Biomechanics, HomeCourt App, Artificial Intelligence, Motion Analysis

1. Introduction

The evolution of AI technology in the past decade has revolutionized performance analysis and training methodology. Currently, all of the sophisticated laboratory equipment, motion-capture studios and professional biomechanical analysts are condensed into powerful mobile technologies with real-time feedback and automated analytics. These trends have rendered AI one of the major disruptive forces shaping modern athletic performance measurement. Amongst all the multitude of sports, basketball, with 450 million competitors worldwide and viewing figures exceeding 2.2 billion, has been significantly influenced by these advances because the success or failure of this sport largely depends on accurate motor skills, fluent biomechanics, and consistent technical performance. Shooting, particularly from 4.5 metres and above, is one of those defining skills that separate run-of-the-mill players from real performers. Since shooting performance is highly sensitive to mechanical consistency, a couple of scholars emphasize the need for quantitative biomechanical feedback to hone shot-making skills.

Biomechanics is the field of study concerned with the action of internal and external forces on the living body and is used to understand athletic movements through scientific approaches to

minimize injury. In basketball shooting, critical biomechanical factors, including release angle, knee flexion, vertical alignment of the target, energy transfer, and follow-through, govern both the effectiveness and repeatability of successful shots. Klem et al. (Klem et al., 2017) investigated the use of lace-up and hinged ankle braces versus no bracing among female basketball athletes using 3D motion capture and force-plate analysis. The findings showed that articulated braces reduced peak ankle inversion and significantly decreased ankle and knee compressive and anterior shear forces, thereby improving prophylactic biomechanics. Vicentini et al. (Vicentini et al., 2025) identified the high-impact nature of basketball, including quick changes in direction, high loads, and biomechanical inefficiencies, as some of the main causes for presenting lower-extremity injuries. Results explained the epidemiology and biomechanics behind frequent injuries, thus illustrating how imaging influences diagnosis, treatment and return to play. Tosarelli et al. (Tosarelli et al., 2024) documented 38 ACL injuries in European professional basketball through video analysis of in-game situations. The results underscore offensive cutting manoeuvres and indirect contact as primary contributors to the risk of ACL injury in elite basketball. Pang et al. (Pang & Zhang, 2025) analysed the DeepLabCut computer-vision model to enhance the accuracy and efficiency of basketball action analysis, thereby overcoming the inherent limitations of conventional subjective and time-consuming biomechanical methods. Results indicate that DeepLabCut achieves better real-time performance, making it an efficient tool for basketball performance and biomechanics analysis. Duan et al. (Duan et al., 2025) analyzed the jump mechanics of 200 basketball players using motion capture and force-plate measurements to assess joint angles, ground-reaction forces, jump height, and speed. The findings suggest personalized strength and technique training programs, which they believe may help improve jump performance and reduce injury based on biomechanical data.

Using machine learning (ML) and computer vision, AI enables advanced motion analysis for athletes (Colyer et al., 2018). AI allows athletes to improve their performance through the analysis of their training data.. AI can give real-time feedback on adjustments to improve performance. Expert systems are an example of artificial intelligence programs used in sports training; this type of AI mimics the decision-making process of a human expert, which can crucially help in sports training, primarily in performance analysis, injury prevention, and customized training programs. Analyzing data using expert systems programs can give athletes insights into strengths and weaknesses, areas of improvement, and ways to improve these weaknesses (Wei et al., 2021). The development of AI-mech applications is game changing for training accessibility. With advancements in pose estimation and motion-tracking neural networks, further supplemented by LiDAR-enabled depth mapping, smartphones can now detect skeletal keypoints and track full-body movements, with virtually no labyrinths of missed connections. Such applications utilise computer vision frameworks, such as You Only Look Once (YOLO), convolutional neural networks, and vSLAM algorithms to estimate patterns of three-dimensional motion. Cheng et al. (Cheng & Cheng, 2024) modelled an AI-based motion detection system for analyzing basketball lower-limb biomechanics by integrating the Harris Hawks optimization algorithm (RHH) with LSTM to enhance time-series biomechanical detection. The study results indicated movement

phases and joint stresses that the system recognized, achieving accuracies of 94.58% and 95.62%, respectively, suggesting that it is sufficient for real-time monitoring and biomechanical analysis of basketball athletes. Bai et al. (Bai & Yang, 2024) integrated sports biomechanics and deep learning to facilitate the prediction of joint injury in basketball training, utilizing improved regression algorithms. Findings indicated its effectiveness in forecasting more reliable injury-risk predictions and is conducive for monitoring athletes' health in contemporary high-intensity basketball programs. Liu et al. (Liu & Pu, 2024) proposed an IB-ASVM for real-time classification of basketball motion states captured by wearable biomechanical sensors. The results demonstrated its effectiveness to detect actions such as taking shots, dribbling, running and pivoting with promising potential for enhancing performance and preventing injury. Min et al. (Min et al., 2024) developed a machine-learning-based joint-injury risk prediction model for basketball players at the University of Xi'an using readily available information, including training load, fatigue, injury history, and anthropometric characteristics. By incorporating records from 100 athletes, the Random Forest model achieved an accuracy of 85% and identified high training load, high fatigue, and a history of injury as independent risk factors. Nagorna et al. (Nagorna et al., 2025) investigated the effect of AI-based data analysis conducted during the 2024 season on the Hudl platform within the lines of activity of the professional Super League team "FRANKIVSK-PRYKARPATTIA." The study highlights the significant benefits of AI in performance, strategy, and injury prevention in today's basketball, with player performance accuracy improving by 87.3%, strategy optimization increasing by 42%, and injury-risk prediction reaching up to 65% accuracy.

HomeCourt, the AI-based shooting analysis app used in this study, is a NextGen/NBA-approved tool that uses augmented reality, neural network processing units, and machine learning models to track release angle, leg angle, release time, trajectory, jump height, and make/miss patterns. Its patents suggest it relies on the iPhone's LiDAR sensor to capture depth and skeletal landmarks, making real-time 3D mapping more accurate than traditional coaching or simple video analysis. However, despite such advances in technology, research on AI-augmented shooting development is mixed. Some studies suggest that form accuracy and decision-making might be improved, while others indicate minimal impact on shooting percentage in real performance, especially among athletes with strong foundational skills. Lai et al. (Lai & Shen, 2025) examined the effects of HomeCourt, an AI-assisted shooting app, on the basketball shooting performance of six Taiwanese collegiate players at various skill levels. The study findings illustrate the effectiveness of HomeCourt in improving both accuracy and engagement around shots, making it a close-to-professional-grade tool for teams unable to afford industry-grade technology. Shah et al. (N. I. Shah et al., 2023) assessed the influence of computerized training on dribbling in a university-level men's basketball team using an agility dribbling test. Study results indicated that computer-based training may substantially improve the dribbling skills of basketball players and support their skill development. Aydemir et al. (Aydemir et al., 2025) analysed a blue-eye-powered AI app that compared vertical jump measurements made by it with those from OptoJump for 12 elite basketball players. The results verify that the DeepSport has valid and reliable performance

measures, making it adequate for both athlete monitoring and coaching applications. Shah et al. (M. Shah et al., 2025) reviewed the impact of big data and AI on sports, including game prediction, tactical analysis, and injury prevention. The study findings provide insight into how knowledge discovery in databases (KDD), logistic regression and neural networks harvest patterns buried in vast data resources for the prediction of outcomes and their strategic consequences. Shang et al. (Shang et al., 2025) evaluated the validity of Maturo, an app for smartphones that calculates biological maturation in 10- to 15-year-old players, demonstrating high validity for PHV speed (ICC = 0.955) and moderate validity for PHV age, with Bland–Altman results revealing no bias. The results reveal Maturo as a valid, low-cost instrument for monitoring growth and maturation, thereby contributing to the safety of youth training programs.

With new technologies advancing at an accelerated pace, there remains a paucity of literature on how mobile AI biomechanics tools affect real-world, immediate changes in basketball shooting performance. In particular, only a limited number of studies have measured both changes in shooting percentage and underlying mechanical variables, such as release angle and leg angle, simultaneously. There is also little evidence comparing AI-based training with traditional forms such as coaching, video instruction, or self-regulated, no-feedback shooting practice. These research gaps should be addressed, as shooting remains one of the most difficult skills to master and a strong contributor to in-game performance.

Therefore, considering the previous studies, this research analyzes the AI-based HomeCourt application to improve accuracy beyond 4.5 meters in basketball shooting over a 35-day training period. The study includes five configurations comprising AI system based training for expert trainees, coach/video-based training for expert trainees, no feedback training for expert trainees as well as combined AI system based and video/coach feedback sessions for novice trainees. It conducts an extensive quantitative analysis of AI's influence across categories of abilities and practice platforms, examining discrepancies in shooting percentage and biomechanical characteristics such as angle of release and leg angle across three comparable testing sessions. With this preface, therefore, the main contributions of this study are:

- Testing of the AI-driven biomechanics platform, HomeCourt, for real-world shooting data and providing direct experimental evidence for influencing not just performance outcomes but also associated biomechanics across a structured period of training.
- Providing insight into the role of AI by demonstrating the rapid conformity to biomechanical standards of non-expert participants, when assisted by AI, this work provides new insight into how AI influence depends on expertise level.
- Facilitation of mechanical efficiency parameters comprising release angle and leg angle for improving short-term accuracy for higher-level players than standard or no-feedback training.
- Evaluation of AI-based analysis for assessing sports-technology interventions through a structured framework that includes experiments, standardized shot routines, and

biomechanics-focused analysis by integrating biomechanics theory, AI data outputs, and performance metrics.

2. Methods and Materials

2.1. Research Design

While traditional advanced biomechanical analysis requires sophisticated laboratory-based motion capture and wearables, recent innovations in mobile technology have enabled similar analyses to be conducted using smartphone applications. This mobile setup provides basketball players with instantaneous and AI-powered feedback on their shooting mechanics without any additional gear. With the widespread use of smartphones nowadays, which now feature high-resolution cameras, it is now possible to capture fine details of human movement, on which biomechanical assessment is based. Video-based applications utilize YOLO (You Only Look Once) object-detection techniques integrated with pose-estimation models to detect and follow skeletal keypoints, which are essential for analyzing joint angles, the body's position and shot mechanics (Figure 1).



Figure 1. YOLO Object Detection

The selected app for this work was HomeCourt, an IA-based basketball training app available only on iOS devices. HomeCourt only works with relatively recent iPhone models because it uses LiDAR (Light Detection and Ranging) technology to improve motion-tracking accuracy. VSLAM (visual Simultaneous Localization and Mapping) algorithms within the app complement the 3D LiDAR sensor to produce a spatially accurate reconstruction of the athlete's motion. LiDAR enables detailed depth mapping, yielding more accurate 3D positional data that enhances the robustness of biomechanical measurements such as release angle, leg angle, or body posture.

After recording raw video and depth data, HomeCourt immediately processes it on-device using neural engines built for machine-learning workloads. The app also provides post-correction analysis by comparing the user's shooting form to biomechanical models of professional players. This enables athletes to see real-time visual and numerical-based feedback on their shooting performance, including trends in made vs. missed shots, ball deviation during shooting, mechanical inefficiencies, etc. The control loop is immediate, allowing athletes to modify technique on the fly.

HomeCourt was selected for this study because it is one of the most sophisticated and popular basketball training apps. Developed by NextGen, the app is tailored for accessibility and usability, as well as for a range of skill levels, making it easy for beginners and seasoned sports stars alike. It does this by incorporating several AI technologies (NLP, predictive analytics, neural networks, AR and computer vision) into a unified platform that generates deep insights and understanding of shooting/dribbling/etc. patterns through the entire body's motion. Figure 2 illustrates how the process behind apps such as HomeCourt works. The use of advanced sensing technology, complemented by machine learning and user-centered design, makes HomeCourt both suitable and effective for evaluating the effect of AI-assisted biomechanics on basketball shooting performance. Figure 3 is a more detailed example of a flow diagram on how data collection and analysis work for a complex system of wearable sensors and motion capture to improve basketball players' performance using AI and ML (Acikmese et al.).

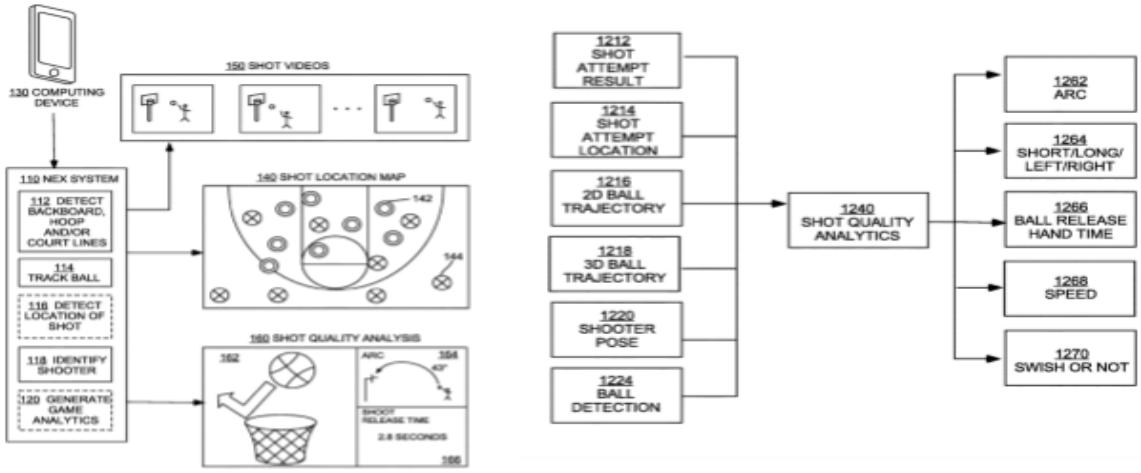


Figure 2. HomeCourt Functionality

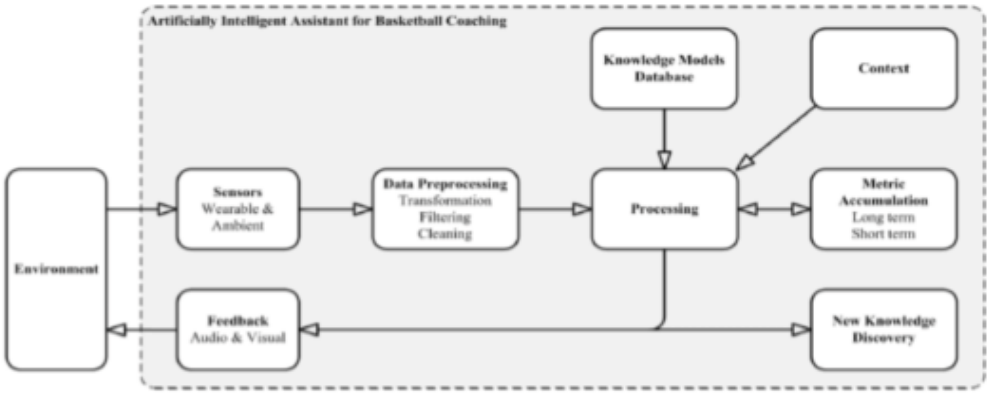


Figure 3. AI systems for basketball (Acikmese et al., 2020)

2.1.1. Research Hypothesis

Participants who train with the AI-powered biomechanic app HomeCourt will improve significantly more than participants who train with guidance and participants who train without shooting feedback. Further, participants' training with guidance should improve more than those without guidance.

Research question: To what extent can basketball AI-powered biomechanics apps help improve players' shooting past 4.5 meters within the period of 35 days?

2.2. Research Variables

2.1.1. Independent Variable:

The type of training method (with or without artificial intelligence–based feedback) applied to participants was the independent variable in this study. Five unique training conditions were created to permit an exhaustive comparison of both experience levels and teaching methods:

- Participants in Group A played basketball and practiced with the AI-trained HomeCourt app, which is used to learn how to play basketball.
- Group B received traditional training via YouTube videos and personal coaching.
- Group C was a control group that trained without any external feedback.
- To compare the AI's effect on beginner athletes, Group D added a novice player who only trained with the HomeCourt app.
- Group E included another beginner training by coaching along with YouTube.

These five variations enabled us to separate the effects of AI assistance from those of coached and self-regulated practices on performance.

2.2.2. Dependent Variable:

The dependent variable was the change of basketball shooting accuracy, which was quantified as the results of three standard shooting tests at day 1, day 28 and day 35 for each experiment. Shooting precision was measured by counting the number of successful and missed attempts in each test. On the days of the dismantling test, each participant practiced a total of 3 × 120 shots on six pre-defined locations on the court:

- left elbow two-points location (5.18 m);
- free- throw line (4.57 m);
- right-elbow two-points location (5.18 m);
- right wing three-point position;
- three-point position at center key and left wing three-pointer point for powerful hand dominant subjects or another location for non-powerful hand dominant participants.

This testing regimen lent itself well to assessing the reliability of performance change between time points and allowed direct comparison of shooting improvement across all training groups.

2.2.3. Controlled Variables:

Numerous factors were controlled to ensure that changes in shooting accuracy are not due to external distractions. Overall training time was equilibrated: to 5.5 and to two hours per week (skipping being added as a missed training day) for Groups A–C and for D–E accordingly. While conditions for individual training environments varied, all official testing was conducted in the same indoor court with similar lighting and low noise. Equipment was also homogenized across test days: all players played with size 7 Spalding Euroleague balls inflated at 8 psi and shot on standard 3.05 m baskets. HomeCourt analyses were obtained using the same iPhone 13 Pro devices affixed to steady tripods at a fixed height (1.5 m). The testing procedure was the same for everyone: 120 shots per player from each of six 'FIBA-points'. Table 1 illustrates the detailed overview of controlled variables.

Lastly, although we were unable to control for baseline physical conditioning, participants were free-living and remained active on average over the 35 days of the study period, thereby minimizing these extensive fitness variations. These controls augmented the internal validity of the experiment and enabled a fair comparison across training groups.

At the beginning of the experiment, on day one, each participant received a set of guidelines to use during training to ensure their safety and injury-free. The experiment raised ethical concerns; on day one, all participants were presented with the experiment and honesty was emphasized. As later explained in the evaluation, not all participants did the same amount of training; however, the training was very similar, and this was crucial since it demonstrated their honesty.

Table 1. Insights of controlled variables

Variable	Reason for Control	Method for Control
Total training time	Ensuring that all participants train for the same amount of time is essential, as it could influence the experiment.	Ensure all participants train for 5 and 1/2 hours (groups A-C) and 2 hours (groups D and E). Also, ensure that if a participant misses a training session, they will make up that training time.
Training environment	Different environments, such as outdoor versus indoor, lighting, or noise, could affect the experiment.	During the training, these environments were challenging to control because every participant trains at different times and locations. During the test days, the environment was similar, with optimal lighting, low levels of noise, and an indoor court.
Equipment Used	Different basketballs, hoops, and courts could influence the experiment.	Although it's challenging to control what basketballs and hoops every participant used during training, the ball and hoop sizes stayed consistent; during the test days, the environment, basketballs, and courts were also consistent. All Basketballs during test days were at eight psi.
Same testing device	The height and type of the phones used to test the participants could affect the experiment.	Two iPhone 13 Pros were used, and the same tripod type was used on both phones, set to a height of 1.5m above ground.
Shots taken	The number of shots taken from different areas during test days and training would affect the experiment.	Due to the lack of resources, the number of shots taken during training was impossible to track. During the test days, the shots were taken from 6 different locations: 30 free throws (4.57 m), 15 two-point shots from the left elbow (5.18 m), 15 two-point shots from the right elbow (5.18 m), 15 three-pointers from the left
Physical condition	Having different participants do different amounts of sports and activities could affect the experiment.	It was impossible to ensure that all participants maintained the same conditioning. However, all the participants were very active during the 35 days.

2.3. Participants

Nine participants were allocated to five groups:

- Group A: three varsity Basketball players who used HomeCourt throughout the 35 days to improve their training.

- Group B: Two varsity Basketball players used YouTube videos and coaching from the school's coach throughout the 35 days.
- Group C: Two varsity Basketball players who received no feedback from HomeCourt or coaching during the 35 days.
- Group D: One participant who had never played basketball and trained with HomeCourt during the 35 days.
- Group E: One participant who had never played basketball was trained with coaching and YouTube videos during the 35 days.

A varsity basketball player in the proposed study was an athlete with more than 3 years of playing experience who devoted more than 2 hours to practice per week, year-round (except holidays). Participants in groups A, B, and C complied with this requirement under a uniform training regimen over the 35 days. These seven subjects belonged to the same basketball team and also took four hours of shooting practice a week, along with their organized 90-minute team practice every Friday. Conversely, beginner participants in Groups D and E only followed a reduced training load, completing two hours of practice per week due to poor experiences. This differentiation permitted relevant and similar workload expectations among experienced and less experienced subjects.

2.4. Experimental Procedure

The following steps were performed for the experiment:

- Deciding which app to experiment with, comparing different groups of individuals shooting.
- In recruiting individuals for the experiment, nine individuals were used, seven of them who play basketball regularly and two who have never played basketball. The Rationale for this recruitment was individuals who would put in the work and wanted to improve.
- Day one: The participants' initial testing is conducted, and everyone's data is tracked using a spreadsheet.
- Regular training will be conducted until the second test day(Day 28). It will last 4 hours a week, plus one and a half hours of basketball training session each Friday for a total of 5.5 hours of training (groups A-C) or 2 hours a week (groups D and E).
- On the 28th day, another test session will be conducted to see participants' progress.
- Continue regular training between test sessions.
- On the 35th day, the final testing of the participants will be conducted.
- Analyze the data and evaluate the conclusions of the experiment using a spreadsheet.

2.5. Material List

- Basketballs used: During the weeks of training, the basketballs used depended on what the contestants had available (but always a size seven basketball); during the shooting test sessions, the basketballs used were always Spalding size 7 Euroleague edition balls 75cm (29.5"). All the basketballs used were at eight psi.
- Two iPhones (iPhone 13 Pro models) were used with HomeCourt for the testing days, and iPhones were used during the basketball training weeks for the four players (Groups A and D) who were using HomeCourt to get feedback.
- Groups B and E used basketball coaches' feedback and YouTube videos on shooting to improve their shooting. Group C had no feedback except for themselves adjusting their shots between makes and misses, trying to get the muscle memory of a made shot.
- Basketball hoops were used. For the three test days, it was at one of the best basketball facilities. The court hoop was primarily used during the training period. All hoops used are set at 3.05m in height with a rim diameter of 46 cm.
- Two tripods were used to hold the iPhones, which were used to record.

2.4. Data Analysis

The statistical analysis of the current study was divided into two main categories: shooting performance results from three testing days and biomechanical data predicted by HomeCourt AI. Figure 4 illustrate the HomerCourt User interface related to shot analysis. As illustrated in Figure 4, shooting performance was measured by recording the number of trials made and missed across three standardized testing sessions (Day 1, Day 28, and Day 35), in which athletes were required to attempt 120 shots per session from six predetermined court locations. This yielded one full set of raw accuracy data for each participant, which was then summed to calculate individual and team-level shooting percentages. This supply of data made it possible to analyze performance progression over the 35 days of practice and to compare performance between the five training groups: AI-trained players, coach-trained players, no-feedback-trained players, and two beginner groups.

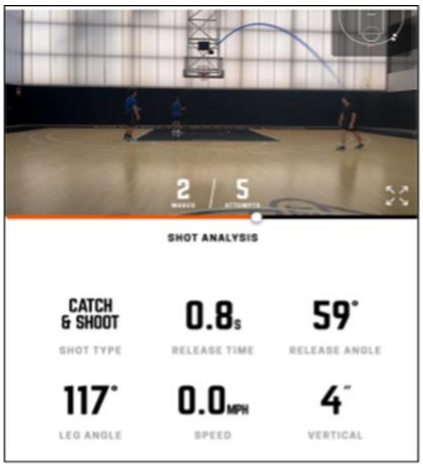


Image Analysis 1

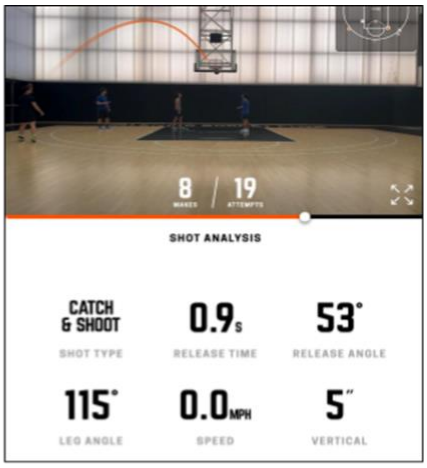


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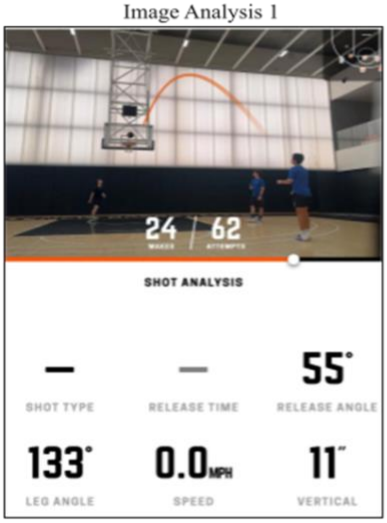


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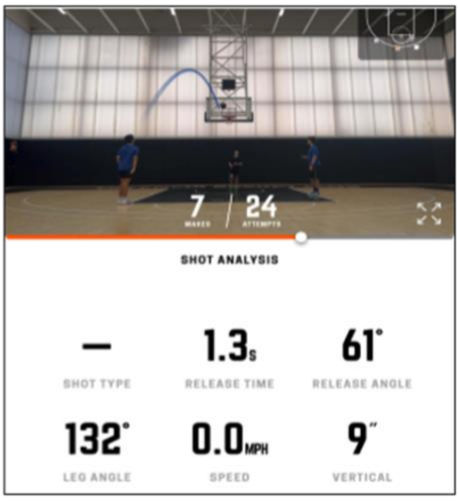


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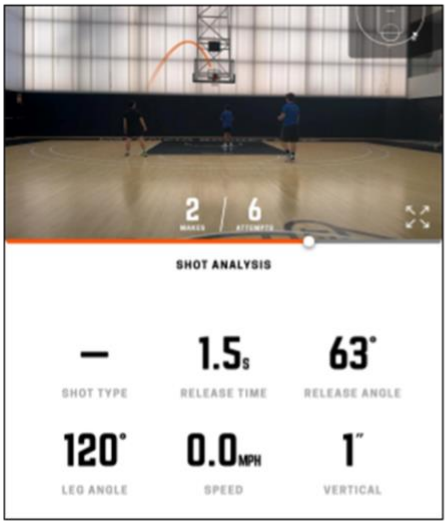


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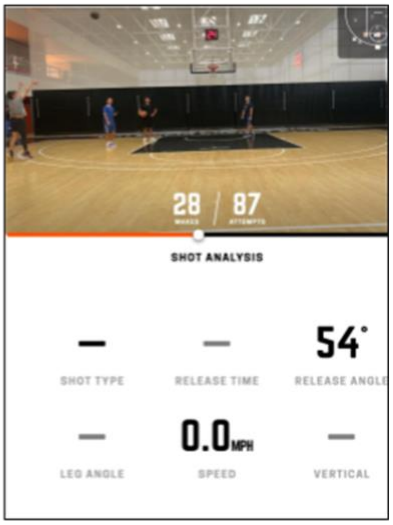


Image Analysis 6

Figure 4. Images of shot analysis through HomeCourt Interface

The second main dataset comprised biomechanical measures collected by the HomeCourt app. Except real-time HomeCourt feedback being provided to only Groups A and D during training where all else was equal, off-court biomechanics data were collected from everyone on both the first and last test days, with complete collectable data stored. HomeCourt usually provides six measurements including shot type, release time, release angle, leg angle, shot speed and vertical jump, but only four were available for analysis: release time, release angle and leg angle (relative to parallel to the ground) in radians along with vertical jump height. After a further reduction in the content domain, only the release angle and leg angle were identified as relevant biomechanical variables for improving shooting accuracy. Shot type was not considered because all shots were catch-and-shoot; release time and ball speed did not play a substantial role in static shot accuracy, and vertical jump height was excluded due to all participants having the same release height.

Home Court records degree release angle and leg angle (to the nearest whole degree), seconds for release time (to the nearest tenth), and inches for vertical height (to the nearest inch). These data contributed to an understanding of the changes in mechanical performance each participant attained during Days 1 through 35. Average release and leg angles were calculated for each participant and compared with previously established optimal biomechanical ranges in basketball shooting research. This facilitated the investigation to expand beyond raw accuracy and explore whether AI-generated feedback helped produce technically efficient shooting motion. Generally, the combination of shooting accuracy trends and biomechanical angle measurements provided a holistic perspective on how distinct training types modulated not only performance outcomes but also underlying shooting mechanics throughout the protocol.

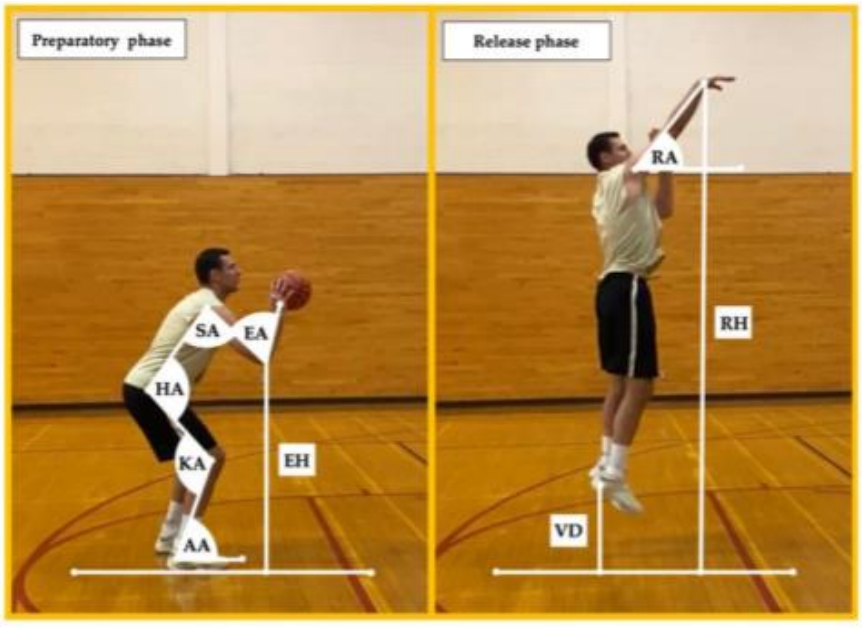


Figure 5. Visual Representation of Measurements (Cabarkapa et al.)

3. Results and Discussion

3.1. Shooting Performance Results

Performance was assessed using raw shooting data collected across all 3 test days, as well as average scores, summarized in the figures provided in this paper. The Processed Chart is an initial graphic representation of a participant's progress and shows each participant's total improvement in shooting accuracy from Day 1 to Day 35. It is clear from this figure that beginners in Groups D and E improved more steeply than novices and master players in Groups A, B, and C; thus, the distinction between beginners and players was the first clear trend in the data set.

Table 2. Shooting percentage of participants in each group

	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
A1	Day 1	26.67%	50.00%	26.67%	0.00%	6.67%	13.33%
	Day 28	53.33%	43.33%	26.67%	20.00%	16.67%	53.33%
	Day 35	46.67%	53.33%	46.67%	40.00%	33.33%	40.00%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
A2	Day 1	33.33%	40.00%	53.33%	26.67%	20.00%	46.67%
	Day 28	40.00%	60.00%	46.67%	33.33%	13.33%	20.00%
	Day 35	40.00%	53.33%	60.00%	46.67%	36.67%	46.67%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
A3	Day 1	33.33%	36.67%	60.00%	0.00%	16.67%	0.00%
	Day 28	20.00%	43.33%	53.33%	20.00%	3.33%	6.67%
	Day 35	40.00%	53.33%	60.00%	40.00%	20.00%	20.00%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
B1	Day 1	53.33%	43.33%	53.33%	26.67%	26.67%	20.00%
	Day 28	60.00%	46.67%	73.33%	33.33%	16.67%	20.00%
	Day 35	53.33%	56.67%	46.67%	53.33%	33.33%	33.33%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
B2	Day 1	6.67%	33.33%	13.33%	26.67%	26.67%	26.67%
	Day 28	33.33%	30.00%	53.33%	33.33%	16.67%	26.67%
	Day 35	40.00%	40.00%	53.33%	33.33%	23.33%	33.33%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
C1	Day 1	26.67%	50.00%	40.00%	46.67%	46.67%	33.33%
	Day 28	33.33%	56.67%	60.00%	26.67%	40.00%	20.00%
	Day 35	40.00%	60.00%	53.33%	60.00%	33.33%	40.00%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
C2	Day 1	20.00%	50.00%	40.00%	20.00%	23.33%	20.00%
	Day 28	43.33%	30.00%	46.67%	26.67%	16.67%	13.33%
	Day 35	66.67%	60.00%	66.67%	46.67%	40.00%	40.00%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
D1	Day 1	13.33%	3.33%	6.67%	0.00%	0.00%	0.00%
	Day 28	20.00%	13.33%	20.00%	13.33%	6.67%	6.67%
	Day 35	26.67%	30.00%	20.00%	13.33%	30.00%	13.33%
	Test Days:	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
E1	Day 1	6.67%	13.33%	6.67%	0.00%	6.67%	6.67%
	Day 28	6.67%	13.33%	6.67%	0.00%	6.67%	13.33%
	Day 35	26.67%	16.67%	26.67%	20.00%	20.00%	20.00%

Table 3. Percentage of shooting of each group in various categories

	Test Days	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
Group A	Day 1	31.11%	42.22%	46.67%	8.89%	14.44%	20.00%
	Day 28	37.78%	48.89%	42.22%	24.44%	11.11%	26.67%
	Day 35	42.22%	53.33%	55.56%	42.22%	30.00%	35.56%
	Test Days	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
Group B	Day 1	30.00%	38.33%	33.33%	26.67%	26.67%	23.33%
	Day 28	46.67%	38.33%	63.33%	33.33%	16.67%	23.33%
	Day 35	46.67%	48.33%	50.00%	43.33%	28.33%	33.33%
	Test Days	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
Group C	Day 1	23.33%	50.00%	40.00%	33.33%	35.00%	26.67%
	Day 28	38.33%	43.33%	53.33%	26.67%	28.33%	16.67%
	Day 35	53.33%	60.00%	60.00%	53.33%	36.67%	40.00%
	Test Days	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing
Group D/E	Day 1	10.00%	8.33%	6.67%	0.00%	3.33%	3.33%
	Day 28	13.33%	13.33%	13.33%	6.67%	6.67%	10.00%
	Day 35	26.67%	23.33%	23.33%	16.67%	25.00%	16.67%

For additional demonstration of progression throughout the study, Group Graphs for Groups A–E compare shooting percentages at Day 1, Day 28, and Day 35 for each shooting location against the other five locations, as shown in Figure 6. These plot graphs provide a visual demonstration of the evolution of performance for each group. For Group A, the curves exhibit rather regular but moderate progress across most positions. There is also a positive trend in group C, supporting the surprising discovery that feedback-less training could improve at nearly the same rate as AI. Statistically, Group B's graphs show abnormal figures and downturns in some cases, consistent with coaching-induced form changes that outpace shooting consistency. The curves for D and E, however, showed sharp inclines across all zones, indicating the accelerated rate associated with beginners just learning basic skills. Figure 7 shows the overall improvement of the shooting performance summed up through the analysis illustrated in Figure 6.

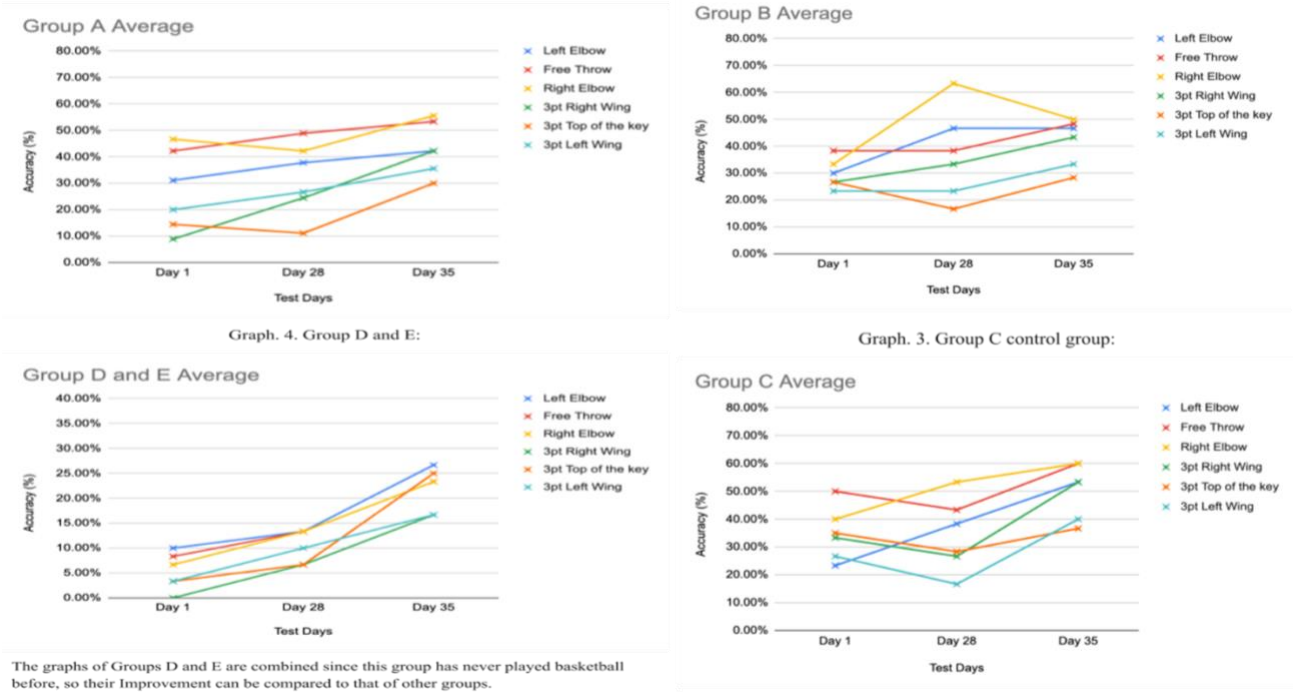


Figure 6. Average shooting accuracy graphs for Groups A-E

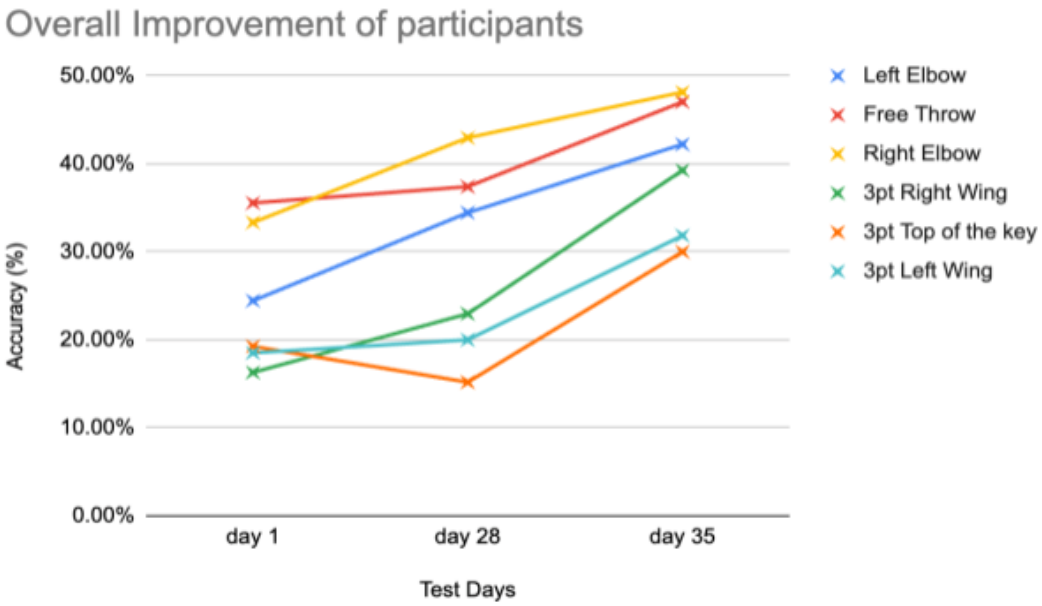


Figure 7. Overall improvement graph of participants

Table 4 illustrates how each group improved over the 35 days. We see that the most significant Improvement, as predicted, was from groups D and E. Since they had never played basketball, learning to shoot would obviously yield the greatest improvement. Mainly, participant D, who was new to basketball and used HomeCourt, both Groups A and Group C showed similar levels of

improvement, with Group A only slightly better. This was surprising and contradicted my hypothesis, indicating that AI or no feedback at all yields the same level of improvement. Additionally, we see that group B had the lowest level of overall Improvement. This is quite common; with coaching and YouTube videos, participants' shooting form changed. As arguably the best shooter of all time, Stephen Curry himself says, “Form… once we started to change it you have to really retrain your brain and your muscle memory and for a month I couldn't, I literally couldn't leave the paint, because I couldn't get the strength to, shoot it out outside the paint” (Bensinger). This shows that even the best shooters struggle to improve when changing form, which explains why Group B didn't improve as much as Groups A and C.

Table 4. Improvement percentage of each group in each of the categories

	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing	Average:
Group A	11.11%	11.11%	8.89%	33.33%	15.56%	15.56%	15.93%
Group B	16.67%	10.00%	16.67%	16.66%	1.66%	10.00%	11.94%
Group C	30.00%	10.00%	20.00%	20.00%	1.67%	13.33%	15.83%
Group D/E	16.67%	15.00%	16.66%	16.67%	21.67%	13.34%	16.67%
Participant D	13.34%	26.67%	13.33%	13.33%	30.00%	13.33%	18.33%
Participant E	20.00%	3.34%	20.00%	20.00%	13.33%	13.33%	15.00%

The unexpected result was with Group A’s Improvement; if we compare participants D and E, we can clearly see that participant D, who was using HomeCourt, improved by over 3% overall. This suggests that artificial intelligence doesn't necessarily help, as some case studies have shown, such as a systematic review of the latest developments in AI-based basketball shooting, which indicates that AI doesn't always improve a single aspect of the game (Yan et al.). Additionally, there may be random errors among participants; participant A2 showed significantly lower improvement than A1, thereby affecting Group A’s overall improvement, as shown in Table 5.

Overall, it is difficult to determine which of the three methods was most effective, as each group showed clear outliers, as shown in Table 5. Analyzing the data in Table 5, Groups A and D improved the most, confirming the hypothesis of the proposed study. This further predicts a more pronounced improvement than the one observed, and it was still more significant than that of the other groups.

Table 5. Improvement percentage of each participant

	Left Elbow	Free Throw	Right Elbow	3pt Right Wing	3pt Top of the key	3pt Left Wing	Average:
A1	20.00%	3.33%	20.00%	40.00%	26.66%	26.67%	22.78%
A2	6.67%	13.33%	6.67%	20.00%	16.67%	0.00%	10.56%
A3	6.67%	16.66%	0.00%	40.00%	3.33%	20.00%	14.44%
B1	0.00%	13.34%	-6.66%	26.66%	6.66%	13.33%	8.89%
B2	33.33%	6.67%	40.00%	6.66%	-3.34%	6.66%	15.00%
C1	13.33%	10.00%	13.33%	13.33%	-13.34%	6.67%	7.22%
C2	46.67%	10.00%	26.67%	26.67%	16.67%	20.00%	24.45%

3.2. HomeCourt Analysis

The HomeCourt analysis covered biomechanical aspects of shooting—release angle and leg angle—for all participants on Day 1 and Day 35. These variables were chosen because they are the most frequently cited determinants of shooting accuracy in the literature. The numbers reported in this section show how the average release and leg angle change between two- and three-point shots for both groups. Table 6 shows that each group more closely approximated the science-based shooting mechanics after 35 days of training.

Based on HomeCourt's internal benchmarks, the release angle would be between 50 and 55 degrees for NBA players taking two-point shots, and their leg angle would be about 115 degrees. These values are supported by further studies: the 180-cm-tall (the height of subjects in this study) players have an optimal range of release angles in between 43 and 47°, wherein a lesser space error occurs, as also seen with a more efficient entry trajectory. This is consistent with previous biomechanical research, including that of Voigt & Fleming on arc angles. Likewise, optimal knee-flexion angles for variation in shot types have been reported in the literature. Cabarkapa et al. d) issues. The authors36 report optimal angles of 121.5° ± 8.8° for free throws, 116.7° ± 7.4° for two-point field goals, and 112.5° ± 7.4° for three-point field goals. For treys, Walker notes that the best shooters let it fly from around 45°.

Comparison of these established guidelines with the HomeCourt data revealed that Group A had already approached perfection mechanically by Day 35. The mean angle of release was 52°, almost as good as the optimal angle found in perfect free throws (50.8°), while their average leg angle was 118°, within the range of normal performance. For two-point tries (FTs and FGs), Group A now once more averaged 118°, close to the recommended 116.7°, while their three-pointer release angle was reduced to an improved 48°, still a little too high (~45°). Thus, the above results

collectively suggest that Group A had the most biomechanically efficient shooting pattern among all groups.

Small improvements were seen on the secondary measures (Groups B and C). Group B inclined 56° on the free throw, not within the ideal range, and group B's leg angle on the two-pointer (110°) was below that in the standard score due to the cumulative effect of the revision of the shot-form. Group C showed more stable two- and three-point release angles, but their three-point release angle was still elevated above the critical level of long-distance shooting (51°). These trends demonstrate that both Groups B and C showed some mechanical improvement, but not to the biomechanical proficiency seen in Group A.

Groups D and E, which had the least-experienced participants, showed different results. Group D (AI-assisted) demonstrated significant improvements, particularly in release angles. On Day 35, their average release angle had increased to 47° – nearly optimal at 45° – while the flight control system prompted changes in the angles between their legs that began to approach the desired values. (Mechanical Development) On the other hand, Group E (coaching-type training) showed uneven mechanical development. One of them is their three-point leg angle, which was 127°, higher than the ideal angle for this shot (i.e., 110º), indicating inadequate knee extension to shoot. Group E: On average, this group showed an increase in shot percentage, but all of it occurred while the associated processes were less effective than in Group D.

On the whole, HomeCourt biomechanics data indicate a difference-maker effect, most pronounced for Groups A and D, in terms of large mechanical changes toward release and leg angles reported to be ideal in other scientific literature. Such data further support the notion that AI-based tools, such as HomeCourt, and others may help players improve their shooting mechanics with instant feedback on Mere seconds from when they actually launched the shot. Crucially, the findings also suggest that novice players could benefit more from AI than professionals, as they could learn correct mechanics from the start rather than retrain past habits. Although AI may lead to only modest short-term gains in shooting percentage, the mechanical changes identified here point to substantial potential for improvement over the long term. This confirms the usefulness of AI-supported training for players seeking structured feedback to improve their shooting technique.

Table 6. Average HomeCourt data for each group

Table. Group A:

Day 1	Release angle	Release time	Leg angle	Vertical
2pts made	59.0	1.3	120.7	6.7
2pts missed	57.7	1.4	119.0	7.3
3pts made	56.3	1.3	119.3	10.7
3pts missed	53.7	1.6	113.7	8.7
Day 35	Release angle	Release time	Leg angle	Vertical
2pts made	52.0	1.0	117.3	8.0
2pts missed	52.0	0.9	120.7	8.7
3pts made	48.3	1.0	116.0	8.3
3pts missed	52.0	1.2	122.0	8.3

Table. Group B:

Day 1	Release angle	Release time	Leg angle	Vertical
2pts made	55.0	0.8	119.5	4.0
2pts missed	56.5	0.8	122.5	3.5
3pts made	50.0	1.0	120.5	8.5
3pts missed	54.5	1.1	118.5	9.0
Day 35	Release angle	Release time	Leg angle	Vertical
2pts made	56.0	0.9	109.5	6.5
2pts missed	55.5	1.1	116.5	8.0
3pts made	51.0	0.8	107.5	7.0
3pts missed	54.5	1.0	113.5	9.0

Table. Group C:

Day 1	Release angle	Release time	Leg angle	Vertical
2pts made	53.0	1.4	122.5	4.5
2pts missed	53.0	1.3	130.0	5.0
3pts made	51.0	0.8	122.0	7.0
3pts missed	57.5	0.9	122.0	8.0
Day 35	Release angle	Release time	Leg angle	Vertical
2pts made	53.5	0.9	122.2	5.0
2pts missed	54.5	0.9	123.6	6.0
3pts made	51.5	0.7	118.7	7.5
3pts missed	58.0	0.8	120.6	7.5

Table. D1. Average Homecourt data for participant D1:

Day 1	Release angle	Release time	Leg angle	Vertical
2pts made	53	2.1	131	2
2pts missed	40	2	163	2
3pts made	0	0	0	0
3pts missed	43	1.8	141	4
Day 35	Release angle	Release time	Leg angle	Vertical
2pts made	49	1	124	5
2pts missed	49	1	118	5
3pts made	47	1.1	119	5
3pts missed	45	1	124	5

Table. E1. Average Homecourt data for participant E1:

Day 1	Release angle	Release time	Leg angle	Vertical
2pts made	46	2.6	153	5
2pts missed	36	1.8	164	2
3pts made	41	3	152	4
3pts missed	40	2.1	150	3
Day 35	Release angle	Release time	Leg angle	Vertical
2pts made	48	1	122	5
2pts missed	46	1	124	6
3pts made	42	1	117	7
3pts missed	43	1	127	7

3.3. Interpretation and Discussion

All in all, the experiment yielded worthwhile input and a portion of the hypothesis was partly confirmed. They were compared with the AI-assisted groups (Groups A and D) on HomeCourt biomechanical measurements and professional shooting standards. It was anticipated that these two groups would perform much better than the others. Although these two groups made significantly greater improvements than the other groups, the improvement was less than we had anticipated. The theory also assumed that when Groups A and B transitioned to a more optimal shooting form, their respective shooting percentages would rise in kind. Nevertheless, this correspondence was not complete, and the proposed hypothesis poorly explained several non-numeric (and psychologically based) factors governing performance.

An important determinant of performance was the quality of the initial shot-form. Many subjects (especially in Group B) began the exercise with incorrect shooting techniques. Aided by a bit of coaching and YouTube-taught technique, they were able to correct their form, but for the next several weeks, found themselves still shooting less consistently. Reductions in performance were also observed in some subjects from Group C, with decreases evident on a few testing days. These oscillations illustrate the well-known phenomenon that mechanical changes often make predictions slightly worse in the short term, even as performance improves.

Additionally, the work was limited to a small number of testing days, three shooting tests and only two days for HomeCourt biomechanical analysis. With so few data points, intersubject variability strongly dominated group-level effects. With that in mind, basketball shooting is very psychological and physically driven; an athlete may shoot lights out one day, but the next day light up the rim. There were also practical problems due to the sample size. Nearly one-half of the participants assigned to only a few clusters hindered an optimal group average. This made it more challenging to recognize true group-level tendency patterns amid individual outliers. The generalizability of such results would increase if more people participated.

Another limitation was the lack of information on training volume. While all subjects were trained for a similar scheduled time, the number of shots fired during each session was neither regulated nor documented. Two players might spend an hour practicing but shoot wildly different numbers of shots, depending on pace, concentration, and fatigue. This lack of uniformity probably accounted for the variable gains between subjects and the low power of group comparisons. Subsequent iterations of this experiment should count (or control for) the number of shots taken rather than just assessing training time.

To conclude, though the observation was that AI-assisted training can indeed make you shoot better, it is more effective for beginners, whose level of improvement will be shaped by several factors. Evaluating more participants, including a longer training period, collecting more data points, and regulating trials would enhance the generalizability of future results and help determine whether biomechanical AI truly affects basketball accuracy.

4. Conclusion

The objective of this study was to determine how much AI-based biomechanics applications, such as HomeCourt, can help improve basketball shot accuracy/mechanics by basketball players over a 35-day training period. The experiment compared athletes who trained with AI feedback, traditional coaching, or no feedback and revealed interesting findings about how different training methods affect performance and biomechanical efficiency.

The findings reveal that all participants improved their performance, and AI-assisted training had the most qualitative benefits for those players in shooting mechanics, particularly regarding optimal release angle and leg angles. These biomechanical enhancements were more pronounced in groups A and D, suggesting that AI tools may more effectively guide players toward evidence-

based movement patterns than coaching or self-regulation alone. In addition, novices received the most aid from the AI and improved more than other groups, both overall in shooting percentage and fastest toward perfect form. This underscores the opportunity for AI-enabled apps to fast-track early skill acquisition through real-time, accurate and personalized feedback.

But the research also found that AI did not lead to significant short-term improvements in shooting accuracy among experienced players. Both groups A (AI) and C (no feedback) improved at nearly the same rate, suggesting that self-correction may also be at play for players with existing mechanics, allowing them to move on without input from outside sources. On the other hand, Group B players (who received coaching and YouTube-based instruction) appeared to experience immediate short-term drops due to mechanics adaptations, as the literature indicates that alternate ingrained motor patterns can cause performance decreases in the short-term.

This study was subject to several limitations: a limited number of participants, only three shooting test days and two biomechanical assessment days available, and mixed training volumes with different numbers of shots taken. These effects probably increased inter-individual variability and diminished statistical discrimination among the groups. By addressing these limitations in future work, such as increasing the number of participants, applying controlled shot counts, and conducting testing over a longer period, stronger conclusions about the long-term efficacy of AI-assisted training could be drawn.

Given these limitations, the study offers convincing evidence that AI-backed biomechanics apps have real value in basketball training, particularly for inexperienced athletes and those seeking quantitative feedback on their technique. Although immediate benefits might not be huge for elite players, the changes in shooting form suggest that AI can have a significant impact over time and help players improve. Overall, this study contributes to the growing body of literature on the use of AI in sports training and how data-driven feedback can enhance the value of traditional coaching for more efficient and effective skill learning in basketball.

Data availability statement

The original contributions presented in the study are included in thearticle; further inquiries can be directed to the corresponding author.

Disclosure Statement

The authors declare that no conflict of interest has arisen in the conduct or reporting of this research. All data acquisition was performed independently, and the authors declare that there we no competing interests or personal relationships that could have appeared to influence the work done in this article.

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