Motor Control of the Baseball-Hitting Technique using Artificial Intelligence Feedback

by

Donghwi Suh [1], Young-Vin Kim [2,]*

This study investigated whether machine learning could classify baseball-hitting techniques and whether artificial intelligence feedback could improve the motor task outcome and movement coordination. For the machine learning model, 48 skilled athletes and 440 novices were recruited. A support vector machine was used as a machine learning method for skill classification. For the pre-test, practice, post-test, and retention tests in motor learning, additional 42 general adolescents were recruited, aside from the already included 488 participants. Motor learning participants were randomly divided into three groups: a control group (N = 14), an artificial intelligence feedback (AIfb) group (N = 14), and a general feedback (Gfb) group (N = 14). Machine learning successfully classified the skill level of baseball hitting. The absolute error of the launch angle was smallest in the Gfb group during the post-test, while the variable error showed the greatest decrease in the AIfb group. The exit velocity was higher in the AIfb than in the Gfb group after practice. The AIfb group exhibited the highest ratio of sequential accelerations among the pelvis-torso-left elbow joints. The number of principal components decreased to three and two in the AIfb and Gfb groups, respectively. As for the loading data, AIfb commonly included the upper limbs, pelvis, and the lower limbs in the group with coordinated movements; for Gfb, after motor learning, the coordination pattern of the lower limbs was eliminated, and the coordination pattern involving only the upper limbs was also removed after practice. Consequently AIfb contributed to improved movement coordination and could effectively change the dynamical degrees of freedom. This technology could benefit coaching in a real-life setting and aid in understanding the human movement coordination structure.

Keywords: *machine learning; motor control; coordination; motor learning; feedback*

Introduction

The prolonged coronavirus disease pandemic has accelerated the development of educational infrastructure incorporating artificial intelligence (AI) (Kang, 2021; Lee and Lee, 2021). Due to the spread of infectious diseases, non-face-to-face education was introduced. To enhance motivation and learning effectiveness in this remote setting, AI-based education integrated with Information and Communication Technology (ICT) is needed. This approach can provide individual learners with the necessary data in real time (Chang et al., 2024). Although this type of non-face-to-face education has the advantage of overcoming spatiotemporal constraints in the era of the global Fourth Industrial Revolution, it can reduce learners' concentration and make interaction between instructors and learners difficult if the necessary data are not provided to individual learners (Varea and González-Calvo, 2021). This challenge is more pronounced in movement education, where individualized movement patterns and the need for expensive real-time analysis tools hinder effective feedback (Rana and Mittal, 2020; Xia et al., 2025). Movement education is essential for a fulfilling life. With the advancement of ICT-integrated education, real-time motion sharing and AI-based learning using big data have become possible (Lee and Lee, 2021; Yuan, 2021). For example, with the popularization

[1] *Department of Practical Physical Education, Daegu Catholic University, Gyeongsan-si, Republic of Korea.*
[2] *Esports, Department of Culture and Arts, Osan University, Osan-si, Republic of Korea.*
* Correspondence: 2025@osan.ac.kr

of devices like smartphones, it has become possible to capture movements at a high frame per second, collect reliable data, and transmit them. Previously, movement data could not be collected in large quantities because it relied on high-end cameras or inertial sensors. However, with the development of ICT as mentioned above, it has become possible to collect big data on biometric information. These raw movement big data cannot directly support learning. To transform it into useful feedback, the data must be classified automatically, analyzed for motor learning and control insights via machine learning, and presented effectively to learners. Such large amounts of motion data and their classification allow for overcoming spatiotemporal constraints and providing automated feedback on appropriate human movement (Yadav et al., 2021).

In order to collect reliable movement data through the camera embedded in the smartphone mentioned in the previous example, the slow-motion function needs to be utilized. By utilizing the slow-motion feature of the smartphone, motion capture of more than 240 frames per second (fps) is possible. To extract kinematic data of joints over time based on video information, filming from multiple angles at a high frame rate or using a depth-perception camera is necessary. However, with the development of motion analysis software that incorporates depth perception by collecting big data on human movement characteristics, videos captured with regular cameras can now be used for motion analysis. Pose landmark detection by MediaPipe (Google, Mountain View, CA, USA) is one such software, and in a pilot test, it showed over 99% accuracy when compared with kinematic data collected by wireless inertial sensors (iSen system, STT, San Sebastián, Spain) for fast and complex motor skills. Complex motor skills are characterized by high perceptual and motor demands, often involving multiple elements and varying environmental interactions (Magill and Anderson, 2021). MediaPipe's pose landmark detection identifies 33 landmarks of the human body, including joints and body parts, and represents them as a 3D animation over time. Through this, it is possible to extract joint positions or velocities over time via a coding program. Therefore a large amount of human movement data can be collected. Once such big data are collected, it must be properly classified to meaningfully identify the characteristics and significance of the movements.

Machine learning can be used as a method to scientifically and objectively classify quantified kinematic data. Among various machine learning techniques, a Support Vector Machine (SVM) is an analysis model that selects support vectors and classifies data, making them suitable for classifying motor performance proficiency. The SVM is a supervised learning algorithm that identifies an optimal hyperplane to classify data, widely used in fields like biomechanics for its effectiveness with high-dimensional data and resistance to overfitting (Begg and Kamruzzaman, 2005; Conforti et al., 2020; Noble, 2006). Previous studies that used the SVM to classify types of movement postures have applied it to simple exercise techniques such as squats or push-ups (Oh and Kim, 2019; Uddin et al., 2022). Those studies achieved high posture-classification accuracy because joint movements were relatively slow. Therefore, this study aimed to examine whether slow-motion functionality could be used to classify the characteristics or proficiency levels of fast and complex motor skills typically seen in sports. Fast and complex motor skills that involve coordinating full-body movements include kicking, throwing, and striking. All of these follow a proximal to distal sequence (PDS) pattern, where movements are sequentially accelerated from the proximal to the distal joints (Putnam, 1993). Among them, striking is one of the most complex motor skill, as it involves the use of a tool, requiring control over the body, and the object to be struck (Müller and Abernethy, 2012). When creating these movements, the complex joints in the limbs interact with each other to maximize the speed of the joints at the extremities of the body, creating dynamic limb movements (Dounskaia et al., 2011; Hirashima et al., 2007). For example, during the baseball hitting technique, experts demonstrated a PDS pattern in which peak angular velocities occurred sequentially in the pelvis, the torso and the left elbow. For novices, this pattern is often inconsistent as multiple joints tend to rotate simultaneously (Chang et al., 2020; Vereijken et al., 1992). Therefore, when classifying proficiency in complex motor skills using machine learning and providing feedback based on it, the coordination structure of movements, which includes these characteristics, must be analyzed. Hitting techniques with these characteristics become more refined during adolescence, a key period for motor learning and physical development (Haywood and Getchell, 2021). Rapid changes in the musculoskeletal system enable skill acquisition, but insufficient motor learning at this stage can hinder hitting technique development, and increase injury risk (Hulteen et al., 2018). Thus, school physical education should appropriately incorporate hitting techniques to support adolescents' long-term engagement in physical activity.

For proper motor learning of hitting technique to occur, appropriate feedback needs to be provided. Although advancements in technology allow us to gather vast amounts of information during the motor learning process, this information must be refined in a way that enables the learner to perceive and comprehend it in order for the learning to be effective. Properly refined feedback helps learners classify data that fall outside conscious perception into meaningful threshold ranges (Sabic and Chen, 2016). This, in turn, facilitates effective motor learning by clearly defining the target value and its acceptable threshold. This can be described as a process where appropriate feedback elicits cognitive processes from the perceived information, leading to enhanced perception-action coupling within the perceptual-motor workspace (Ong and Hodges, 2020). Perception-action coupling refers to the continuous and reciprocal interaction between sensory information and motor responses, enabling adaptive movement. The perceptual-motor workspace represents the dynamic range of sensory and motor possibilities within which individuals explore and refine actions. Effective feedback that supports perception-action coupling and exploration within the perceptual-motor workspace varies depending on the goal (Sigrist et al., 2013). This can be divided into the improvement of the motor task outcome and movement coordination. Information directly related to these two goals is called "knowledge of results" (KR) and "knowledge of performance" (KP) in motor learning. KR pertains to external information that provides participants with the outcomes of the motor task in motion, while KP refers to information about the characteristics of actual performance or movement with respect to the environment (Oppici et al., 2021). KP was found to be more effective than KR when the perceptual-motor workspace was activated to solve the goal of motor learning (Oppici and Narciss, 2021). For feedback to be guided to the perceptual-motor workspace in novices, KP was found to be effective when it was prescriptive relative to the goal of motor learning (Lawrence et al., 2011; McErlain-Naylor et al., 2021; Newell, 1991). Therefore, feedback on hitting techniques should provide information on improving motor task outcomes and movement coordination using the methods mentioned above.

In hitting technique, motor task outcomes are determined by the exit velocity and the launch angle, but considering movement coordination, changes in it need to be observed. In the dynamical systems approach to motor control, changes in coordination can emerge from the interaction of multiple constraints (e.g., organism, task, and environment), reflecting the influence of Bernstein's foundational ideas on movement variability and self-organization (Bernstein, 1967). Human coordination varies according to the motor learning stage, and the level of motor skill performance is determined by how effectively extra degrees of freedom are utilized and coordinated (Burton and Rodgerson, 2001). This indicates that the movement changes efficiently through coordination by adjusting the degree of freedom with the automation of movement. Degrees of freedom refer to the number of independent joint or limb movements that can be functionally regulated during motor execution. While the number of potential movement possibilities in the human body is theoretically infinite, the relevant degrees of freedom are understood within specific biomechanical or neurophysiological constraints. Depending on the analytical perspective, these can be classified as mechanical degrees of freedom (e.g., anatomical joint mobility) or dynamical degrees of freedom (e.g., coordinated units of movement that emerge during task execution). During motor execution, the central nervous system manages this complexity by constraining or coupling multiple elements to simplify control, often through processes such as synergies or self-organization. Mechanical degrees of freedom refer to the degrees of freedom at the joint level, representing the movement of a joint that rotates in three dimensions (3D). They are defined by the number of independent axes around which a joint can rotate. In contrast, dynamical degrees of freedom refer to the number of functional movement variables that emerge from the coordination of multiple mechanical degrees of freedom as they are expressed during movement in space and time. These represent the organization of mechanically possible movements into coherent coordination units, or synergies, each functioning as a single dynamical degree of freedom. In this context, principal component analysis (PCA) is used to identify linear relationships among multiple variables and reduce dimensionality, thereby revealing the dynamical degrees of freedom (Hong and Newell, 2006). Therefore, appropriate feedback based on the above refined information is required to improve the motor task outcome and movement coordination of the hitting technique.

Regarding General Feedback (Gfb), the learner's kinematic information is directly observed by a professional baseball coach or a physical education teacher and provided through verbal feedback. Since this process relies on subjective interpretation rather than objective measurement, there are inherent limitations in accurately processing and analyzing such a large amount of data. Considering the diverse movement patterns involved in complex motor skills, AI should be designed to extract and classify biomechanical features such as joint angles, angular velocity, and timing sequences that are relevant to motor task outcomes and movement coordination. These features should then be translated into clear and understandable feedback that learners can easily perceive and apply (Power, 2014). Artificial intelligence feedback (AIfb) enhances motor task outcomes and movement coordination by automatically analyzing real-time motion videos and providing task-relevant information without causing perceptual overloading within the learner's perceptual motor workspace. Drawing on significant coordination patterns identified through PCA of large-scale movement data, researchers and coaches pre-construct feedback cues that the AI system uses to deliver meaningful and easily interpretable information to learners. This process is ensured through algorithms that identify repetitive patterns and effectively reduce the dimensionality of large datasets in a statistically significant manner. The resulting prescriptive KP and KR can be automatically categorized as feedback and provided to learners. In other words, AI feedback can refine real-time biomechanical data to automatically analyze incorrect motor task outcomes or movement coordination in movement and provides appropriate feedback.

This study aimed to develop effective AI-supported physical education by creating a model to classify and discriminate between movements and give feedback through machine learning for hitting technique. Herein, we transformed baseball hitting technique into big data and classified these skills using machine learning. We conducted two experiments in this study. The first experiment aimed to classify the proficiency of the hitting technique using machine learning. The second experiment examined the effectiveness of motor learning and control in novice learners when provided with AIfb. This AIfb was developed through discussions with a professional baseball coach and a PhD specializing in motor learning and control, based on the characteristics of kinematic data used to classify skill levels. It provided real-time, automated feedback by offering quantitative KR on the motor task outcome in the form of the launch angle, and prescriptive KP on movement coordination by informing joint movement relationships within each swing segment, which were categorized as a back swing, a front leg stride, a forward swing, and sequential acceleration of the pelvis, the torso, and the left elbow. This was designed to facilitate perception action coupling in adolescents. In this study, movement coordination was operationally defined as the spatiotemporal organization of joint actions across distinct swing segments, with particular emphasis on the sequential acceleration of the pelvis, the torso, and elbow joints—a pattern commonly referred to as the PDS pattern. Furthermore, grounded in dynamic system principles, movement coordination was conceptualized as the process by which the central nervous system constrained and organized the available dynamical degrees of freedom into stable, task-specific movement patterns. This adaptive regulation facilitated the efficient production of bat speed and the emergence of optimized swing mechanics, particularly through the temporal coupling and sequencing of body segments. Based on this definition, the dependent variables for movement coordination were set as the presence of the sequential acceleration and the number of principal components (N_{PC}), representing the dynamical degrees of freedom within coordination patterns. Therefore, in the experiment of machine learning, we expected that the proficiency in the complex motor skill of hitting could be classified through machine learning using videos filmed in this manner. In the motor learning and control experiment, we expected that improvement in the motor task outcomes would be greater through AIfb, which provided quantitative feedback on the launch angle, rather than feedback from a coach (Gfb). Similarly, for movement coordination, we anticipated that improvement would be more significant when using AIfb, which provided immediate and quantitative feedback on joint movements within categorized swing segments, namely the back swing, the front leg stride, the forward swing, and the sequential acceleration of the pelvis, the torso, and the left elbow, rather than relying on the coach's intuitive feedback (Gfb). We set out to test the following hypotheses:

(1) (Experiment 1) Machine learning using the SVM technique would successfully classify the proficiency level of baseball hitting movements.

(2) (Experiment 2) The motor task outcomes were expected to be improved to a greater extent in the AIfb group compared to the Gfb group.

(3) (Experiment 2) Movement coordination was expected to be improved to a greater extent in the AIfb group compared to the Gfb group.

Methods

Participants

In the study verifying the machine learning model, 488 adolescent males (15.04 ± 1.03 years) participated. Of these, 48 were skilled baseball players and 440 were novices. An a priori power analysis using G*Power (two-tailed *t*-test, α = 0.05, power = 0.95, effect size = 0.5) indicated that a total of 134 participants would be sufficient to detect medium group differences. The total sample in this study far exceeded that number, ensuring adequate statistical power. Unlike the skilled baseball players, the novice group required a larger sample to capture the wide range of variability inherent in motor skill acquisition, which is critical for training a robust machine learning model. The resulting class imbalance was addressed through appropriate evaluation metrics such as the F1-score, which balanced precision and recalled to ensure that the model's performance on the smaller skilled group was accurately assessed despite the data imbalance. We obtained written informed consent from the participants and their guardians before the experiment, and the study was approved by the Institutional Review Board of the Seoul National University, Seoul, South Korea (approval number: 2210/002-016; approval date: 13 October 2022).

In the study of motor learning using AIfb, a total of 42 adolescents between the ages of 13 and 15 with no neurological, physical, cognitive, or mental conditions participated. Participants were randomly divided into three groups: 14 participants each in the control group, the AIfb group, and the Gfb group. The minimum sample size of 24 participants was calculated for a repeated measures ANOVA with within-between interaction using G*Power (version 3.1.9.4) (Katsumata et al., 2017), with α = 0.05, power = 0.95, and effect size = 0.40. We included 42 participants in the study to ensure greater statistical power, enhance the robustness of the results, and account for potential attrition or data variability.

Measures

In this study, the baseball hitting technique referred to striking a tee ball placed on a batting tee to achieve the maximum possible distance, primarily determined by the launch angle and exit velocity. A tripod and a camera (Galaxy S9, Samsung, Suwon-si, Korea) were positioned at the same height as the batting tee, 3.5 m directly in front of the participant's torso, facing them to capture a frontal view. The height of the batting tee was set at the iliac crest of the participant.

The experiment was conducted through motion analysis and proficiency screening programs developed using MediaPipe (Google, Mountain View, CA, USA) and Python 3.10 (Python Software Foundation, Wilmington, DE, USA). The baseball hitting was filmed in slow motion on a Samsung Galaxy S9's rear camera at 240 fps. In the following motor learning experiment, 16 3D wireless inertial sensors (iSen system, STT, San Sebastián, Spain) were additionally utilized. Angular data from body segments were collected at 400 Hz by attaching wireless sensors to relevant anatomical locations including the forehead, the sternum, the fifth lumbar vertebra, upper arms, forearms, backs of the hands, quadriceps, shins, insteps, and the tee ball bat using straps to minimize motion artifacts.

After machine learning was completed, the variables that differentiated skilled athletes from novices were classified into the back swing, the front leg stride, the forward swing, and the sequential acceleration of the pelvis-torso-left elbow. These categories were derived from an AI-based full-body kinematic analysis conducted during a preliminary pilot study. In this phase, AI was used to process and extract relevant movement features using dimensionality reduction techniques such as PCA. The AI system then identified and prioritized feedback variables based on their contribution to performance differentiation and motor learning outcomes. Among these, the sequential acceleration of the pelvis-torso-left elbow was consistently highlighted as a core indicator, leading to its inclusion in the final feedback design. Thus, although the final feedback may appear simplified, it is in fact the result of a data-driven, AI-supported decision process aimed at optimizing feedback relevance and minimizing the cognitive load for novice learners. This pattern in which the peak angular velocities of the pelvis, torso and left elbow occurred in sequence was commonly observed in skilled athletes and also served as a perceptually salient and actionable feedback cue for novice learners. To provide the classified variables as AIfb, proprioceptive and visual cues from professional baseball coaches interviewed in advance were created and matched to allow adolescents to recognize and understand them. Furthermore, motor learning was conducted to improve the motor task outcomes and movement coordination.

Design and Procedures

Verification of Machine Learning

Baseball hitting video data were collected through MediaPipe and their reliability was verified by classifying proficiency through machine learning (Figure 1). Participants hit the tee ball ten times in one block. Data included positions and velocities of segments over time in baseball hitting, as well as angular data of joints, along with velocities and angles of a ball when hit. The kinematic data of 29 joints were analysed using the PCA code of the MATLAB program (Mathworks, Inc., Natick, MA, USA), and the PCs corresponding to the number of values that accounted for 90% of the total PC variance were found, where the PC score was used in the SVM algorithm module to perform machine learning. To effectively reduce dimensionality while preserving essential information, we selected principal components (PCs) that accounted for 90% of the total variance. While the eigenvalue threshold method (Kaiser criterion) is commonly used, it may not be optimal for high-dimensional kinematic data, as it can retain too many or too few components. Considering the application of the Support Vector Machine (SVM) in our study, using the 90% explained variance criterion provided a more appropriate dimensionality reduction strategy. This approach ensured that sufficient variance was retained while reducing computational complexity and improving model generalization. One dataset for executing the SVM was linearly interpolated data of 50 for 29 joints over time, arranged in 1 row × 1,450 columns. The 29 joint angles and relative segment positions observed during the swing phase were linearly interpolated to 50 points over time. In a pilot test, the slowest participant's swing lasted less than 500 ms, resulting in an effective extraction rate of over 100 frames per second. The dataset for machine learning consisted of 3,080 cycles for novices and 340 cycles for experts. These data were generated from 3,080 cycles, with 308 out of 440 novices each performing 10 swings. Out of 48 experts, 34 performed 10 swings, generating a total of 340 cycles of data. The remaining data were used to validate the reliability of the machine learning model. Specifically, 1320 cycles of novice data from 132 novices and 140 cycles of expert data from 14 experts, each performing 10 swings, were used. Based on previous research suggesting that a 7:3 ratio is appropriate for dividing datasets for machine learning and validating reliability, the data were randomly split accordingly (Nalepa and Kawulok, 2019). The data were constructed by comparing the feature points used in the proficiency classification model of hitting skills (Power, 2014).

Motor Learning and Control Procedure

Pre-Test

A professional baseball coach provided preliminary training to the participants on feet positioning, grip, swing, and hitting. Participants then watched an expert demonstrate hitting ten balls from a tee at 8-s intervals, aiming for maximum distance, and practiced twice. Each individual hit a total of ten balls as far as possible at 8-s intervals from a designated location (Figure 2).

Learning Phase

The learning phase was conducted over five days and participants were allowed to hit five blocks/day. One block consisted of hitting ten tee balls as far as possible, with the ideal launch angle set to 29° (24°–34°; the average launch angles for home runs in the major leagues) (Katsumata et al., 2017). Accordingly, all participants in the three groups were instructed to hit the tee ball as far as possible and were informed that the ideal angle for achieving this was 29 degrees, so they should aim to match that angle. After hitting two tee balls, each group received tailored feedback only for the second ball, i.e., five times per block, with a 3-min rest interval between blocks. This is because providing feedback after multiple attempts allows learners to better self-regulate and refine their skills over time (Schmidt, 1991). During the practice phase, motor learning was conducted through self-paced learning. For AIfb, when the movement coordination was satisfied, the prescriptive KP about the sequential acceleration of the pelvis-torso-left elbow, which was the movement coordination goal, and KR on the launch angle were provided. Movement coordination was considered to be satisfied when all four swing segments (the back swing, the front leg stride, the forward swing, and the sequential acceleration) were performed correctly as defined in Table 1. When movement coordination was unsatisfactory, prescriptive KP and KR on the launch angle were provided to improve the back swing, the front leg stride, the forward swing, or the sequential acceleration (Table 2). The prescriptive KP was designed to improve the execution of the back swing, the front leg stride, and the forward swing, and to ensure that sequential acceleration occurred in the correct order: the pelvis, the torso, and then the left elbow. Table 1 shows the dissatisfaction criteria for movement coordination. When there were several insufficiencies, one piece of prescriptive KP on the part in which the error occurred first in the sequence of motions was provided. In this study, KP and KR provided by AIfb were delivered in Korean via a computer-generated voice.

As for Gfb, a professional baseball coach directly observed learners and presented prescriptive KP about movement and KR, such as the launch angle, as verbal feedback for the movement coordination and motor task outcomes (Table 2). Gfb's prescriptive KP was discussed with professional baseball coaches to provide it in the categories of the back swing, lower limb movement, the forward swing, and the sequence acceleration movement. For the control group, participants were instructed to aim for a 29-degree launch angle when hitting the tee ball as far as possible. They completed the same number of hitting and rest sessions but did not receive any external feedback.

Post-Test

The post-test was carried out with sufficient rest (up to 15 minutes) after completing the learning phase. One block was performed by hitting ten tee balls at intervals of 8 s.

Retention Test

The retention test was conducted 48 h after completing the learning phase, following the same procedure as the post-test.

Experimental Design

This study utilized a two-factor mixed model in which three groups and three test sessions were independent variables. In addition, the results of the motor task, specifically the accuracy and consistency of the target launch angle and the exit velocity of the hit, were used as dependent variables. The model was designed with the ratio of sequential accelerations representing movement coordination, along with the N_{PC} of the joint angles and segmental movements.

Data Analysis

This analysis, which used a confusion matrix to evaluate machine learning algorithms, corresponded to the first experiment. The performance index of the machine learning model could be obtained as follows, and the F1-score was used as an index to evaluate the performance of the machine learning model (Miao and Zhu, 2022).

$$(1)\ \text{Precision} = \frac{True\ positive}{True\ positive + False\ positive}$$

$$(2)\ \text{Recall} = \frac{True\ positive}{True\ positive + False\ negative}$$

$$(3)\ \text{F1-score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Improvement in motor learning outcomes, confirmed by the exit velocity and the launch angle of the ball, was observed in the second experiment. Movement coordination was defined based on the requirements of the experimental design. In the context of baseball hitting, it referred to the sequential acceleration of the pelvis, torso, and elbow joints, known as the PDS pattern. Additionally, from the perspective of the dynamic systems theory, it was conceptualized in terms of the number of coordination units formed by the dynamical degrees of freedom. Accordingly, the movement coordination was confirmed using the ratio of the maximum angular velocity occurring in the order of the pelvis-torso-left elbow (ratio of sequential acceleration) and the N_{PC}. The ratio of sequential accelerations represented the ratio of the number of strikes, out of 10 strikes, where the maximum angular velocity of the three aforementioned joints occurred sequentially. N_{PC} was identified as the number of the PCs where the variance (latent) explained by the principal components exceeded 90%. This referred to the dynamical degree of freedom, which was the number of coordination groups that had the greatest influence among the movements of segments affecting multi-joint actions and movements. The dependent variables of the motor learning and control study (second experiment) were the accuracy and consistency of the target launch angle, exit velocity, the ratio of sequential accelerations, and N_{PC}.

Data from the wireless inertial sensor used to analyse whole-body movement in the baseball-hitting experiment were filtered with a fourth lower pass Butterworth filter. Fast Fourier transformations were used to set the upper limit for the frequency of movement. The frequency at which power spectrum density occupied 99% was 10 Hz, which was set as the cut-off frequency.

Key Variable Calculation

The target launch angle was 29°. Accuracy was measured by determining the angle at which the hit ball was launched from a plane created based on the horizontal axis (direction of hitting) and the vertical axis in a 2D space. The target launch angle used in the calculation was 29°. Absolute error (AE) was used for accuracy (Equation 1).

Equation 1. AE $=\sum|x_i - T|/n$

[x_i = launch angle at the i th hit, T = 29°, n = total number of trials]

For consistency, we used the variable error (VE), which was calculated using the difference between each trial's launch angle and the average launch angle across trials (Equation 2).

Equation 2. VE $=\sqrt{\sum(x_i - M)^2/n}$

[x_i = launch angle at the i th hit, M = average launch angle, n = total number of trials]

Exit velocity was determined by measuring the velocity of the hit ball in 3D using a speed measurement program (Kinovea 9.3, Kinovea.org, France), with the results expressed in km/h. The flexion, abduction, external rotation, and counter-clockwise rotation of the joint was set as the (+) direction, and measured using the wireless inertial sensor (iSen system, STT, San Sebastián, Spain). The linear movement (medial-lateral) of the segment in the direction of the intended ball strike was set as the (+) direction and measured using the MediaPipe program (Google, Mountain View, CA, USA). The onset of the swing section (t_0) was defined as the point at which the knee angle of the leading leg exceeded ten times the standard deviation (SD) of the mean value during the stable state. This was because the degree of knee flexion in the lead leg varied among the skilled athletes measured in the pilot test. To encompass this variability, the onset was defined as the point where the knee flexion exceeded 10 standard deviations from the average knee angle in each participant's stable state. The stable state was a condition where research participants held the stance in preparation for hitting and waited for 3 s. For novices, they were required to initiate the swing through knee flexion in the lead leg. This approach allowed for the valid establishment of the onset for all participants in the study. The end of the swing section was determined as the elbow of the arm holding the lower part of the bat (the left arm for right-handers) was maximally extended after impact.

The sequential accelerations meant the order of time when the rotational angular velocity of the pelvis, the torso, and the angular velocity of the elbow joint were maximized. PCA was used based on the calculated joint angle and segment position data (Federolf et al., 2013). Table 3 shows the joints and segments used for PCA. Data from the first to the 28^{th} consisted of angle data over time, and the data from the 29^{th} consisted of the relative position (distance in meters) of the left foot to the right foot in the direction (x-axis) of hitting the ball over time. The 29 joint angles and relative segment positions observed during the swing phase were linearly interpolated to 50 points over time. In a pilot test, the swing of the participant who performed the slowest swing took less than 500 ms, and the data were collected using an inertia measurement unit at 400 fps. Therefore, data interpolated to 50 samples for swings performed in less than 500 ms could validly correspond to the data collected at 400 fps. This allowed for the creation of a 50 × 29 matrix, which was then converted into a 29 × 29 correlation matrix. The eigenvectors and eigenvalues of the correlation matrix were calculated to find the PC values mainly occupied by the eigenvalues among the 29 PCs.

Statistical Analysis

In this study, statistical analysis was performed using GraphPad Prism 7.0 (GraphPad Prism Software Inc., San Diego, CA, USA). The level of statistical significance was set at $p < 0.05$. Two-way ANOVA with repeated measures on the second factor was used to compare the accuracy and consistency of the launch angle, exit velocity, and the ratio of sequential accelerations according to the group and the test session, followed by a post-hoc Tukey's multiple comparison test if there was a significant difference. The N_{PC} in the joint coordination structure was tested using the Kruskal-Wallis test for comparison between groups and the Friedman test for comparison between test sessions. Post-hoc analysis was performed using the Dunn's multiple comparison test.

Results

Verification of Machine Learning

Confusion Matrix

The machine learning model using the SVM technique successfully classified the proficiency level of baseball hitting movements into two groups. The confusion matrix resulting from the verification of machine learning was as follows: the F1-score was set at 0.98, as an index for performance evaluation of the machine learning model. This was calculated based on the following classification results: 1,310 true positives (novices correctly classified as novices), 10 false negatives (novices incorrectly classified as skilled), 33 false positives (skilled participants incorrectly classified as novices), and 107 true negatives (skilled participants correctly classified as skilled).

Motor Learning and Control Experiment

Motor Task Outcomes

Contrary to the second hypothesis presented in the Introduction, the group that received Gfb showed a greater reduction in AE (indicating improved accuracy) than the AIfb group in the post-test. However, there was no significant difference among the groups in the retention test. The accuracy of the launch angle, calculated using AE, was compared across different tests or groups (Figure 3a). In the main effect for the group, the difference in launch angle accuracy was not significant [$F(2, 39) = 2.075$, $p = 0.1392$, $\eta^2 = 0.182$]. However, there was a significant difference in the main effect for the test session [$F(2, 78) = 17.54$, $p < 0.001$, $\eta^2 = 0.994$], as well as in the interaction effect [$F(4, 78) = 3.806$, $p < 0.01$, $\eta^2 = 0.677$]. Post-hoc analyses were conducted to explore the specific nature of this interaction, revealing significant differences between groups at certain time points. In a post-hoc analysis by group, the Gfb group exhibited a significantly lower AE compared to the control group, and the AIfb group in the post-test (post-test = Gfb-control: $p < 0.05$; Gfb-Afb: $p < 0.001$). In a post-hoc analysis by test session, the control group exhibited a significantly lower AE in the retention test compared to the pre-test, and lower AE in the post-test compared to the pre-test (control = post-pre: $p < 0.05$; retention-pre: $p < 0.01$). In the AIfb group, the AE was significantly lower in the post-test than in the pre-test (AIfb = post-pre: $p < 0.05$). In the Gfb group, the AE was significantly lower in the post-test than in the pre-test, and the AE in the post-test was significantly lower than in the retention test (Gfb = post-pre: $p < 0.001$; post-retention: $p < 0.01$).

Contrary to the second hypothesis, there was no significant difference between the two feedback groups. Overall, compared to the pre-test, VE decreased in both the post-test and the retention test, indicating improved consistency. The consistency of the launch angle was compared based on the size of the difference in the launch angles of each individual. Figure 3b shows differences according to each group and test session. In the main effect of the group, we found no significant differences in consistency (VE) of launch angles [$F(2, 39) = 2.314$, $p > 0.05$, $\eta^2 = 0.026$]. Similarly, the interaction effect between the group and the test session was not significant [$F(4, 78) = 0.722$, $p > 0.05$, $\eta^2 = 0.182$]. There was a significant main effect of the test session [$F(2, 78) = 68.923$, $p < 0.001$, $\eta^2 = 0.532$]. Meanwhile, the simple main effects revealed that VE was significantly lower in the post-test and the retention test compared to the pre-test (post-pre: $p < 0.001$; retention-pre: $p < 0.001$).

As proposed in the second hypothesis, with regard to exit velocity, which is a key determinant of motor task outcomes, the AIfb group demonstrated significantly greater improvement than the Gfb group in both the post-test and the retention test. Figure 3c shows the difference in the exit velocities, according to the group and the test session. In the main effect test for the group, we found significant differences in the exit velocities [$F(2, 39) = 62.84$, $p < 0.001$, $\eta^2 = 0.444$], the main effect test for the test session [$F(2, 78) = 53.05$, $p < 0.001$, $\eta^2 = 0.833$], and the interaction effect for both the group and the test session [$F(4, 78) = 14.27$, $p < 0.001$, $\eta^2 = 0.199$]. In the post-test during the post-hoc analysis, the AIfb and Gfb groups had significantly higher exit velocities than the control group, while the AIfb group had a significantly higher exit velocity than the Gfb group (post-test = AIfb-control: $p < 0.001$; Gfb-control: $p < 0.001$; AIfb-Gfb: $p < 0.01$). In the retention test, the AIfb and Gfb groups had significantly higher exit velocities than the control group, while the AIfb group had a significantly higher exit velocity than the Gfb group (retention test = AIfb-control: $p < 0.001$; Gfb-control: $p < 0.05$; AIfb-Gfb: $p < 0.001$). Furthermore, the AIfb group was found to have a significantly higher exit velocity in the post-test and the retention test than in the pre-test, and in the post-test than in the retention test (AIfb = post-pre: $p < 0.001$; retention-pre: $p < 0.001$; post-retention: $p < 0.01$). The Gfb group had a significantly higher exit velocity in the post-test and the retention test than in the pre-test, and in the post-test compared with the retention test (Gfb = post-pre: $p < 0.001$; retention-pre: $p < 0.05$; post-retention: $p < 0.001$).

Movement Coordination

As proposed in the third hypothesis, the AIfb group showed a higher ratio of sequential acceleration, which is a variable related to movement coordination, compared to the Gfb group. The ratio of sequential accelerations according to the test session and the group was identified (Figure 4a). As a result of the analysis, the difference in the main effect for the group [$F(2, 39) = 4.38$, $p < 0.05$, $\eta^2 = 0.647$], and the difference in the main effect for the test session [$F(2, 78) = 4.355$, $p < 0.05$, $\eta^2 = 0.957$] were significant. The interaction effect, according to the group and the test session, was not significant [$F(4, 78) = 2.05$, $p > 0.05$, $\eta^2 = 0.891$]. Meanwhile, the simple main effects for the group revealed that the ratio of sequential acceleration was significantly higher in the AIfb group compared to the control group and the Gfb group (AIfb-control: $p < 0.01$; AIfb-Gfb: $p < 0.05$). The simple main effects for the test session revealed that the ratio of sequential acceleration was significantly lower in the pre-test compared to the post-test and the retention test (pre-post: $p < 0.05$; pre-retention: $p < 0.05$).

Contrary to the third hypothesis, there was no significant difference between the two feedback groups in the N_{PC}, which reflects the dynamical degrees of freedom in movement coordination. However, only the feedback groups showed a significant reduction in the number of components. PCA was conducted on the time-dependent movements of 29 joints during a baseball swing. The N_{PC}, which represents the number of the first PCs where the cumulative variance exceeds 90%, was analyzed using non-parametric statistics through its mode (Figure 4b). There was a significant difference in the N_{PC} based on the group [X^2(df = 2; N = 42) = 34.5837, $p < 0.001$, $\eta^2 = 0.220$].

The post-hoc analysis found that in the post-test, the AIfb and Gfb groups had a significantly smaller N_{PC} than the control group (AIfb-control: $p < 0.001$; Gfb-control: $p < 0.001$). The post-hoc analysis found that in the retention test, the AIfb and Gfb groups were found to have significantly fewer PCs than the control group (AIfb-control: $p < 0.01$; Gfb-control: $p < 0.001$).

There was a significant difference in the N_{PC} based on the test session [X^2(df = 2; N = 42) = 39.217, $p < 0.001$, $\eta^2 = 0.467$]. According to post-hoc analysis, the AIfb group had a significantly smaller N_{PC} at the post-test and the retention test than at the pre-test (post-pre: $p < 0.001$; retention-pre: $p < 0.001$). The Gfb group also had a significantly smaller N_{PC} at the post-test and the retention test than at the pre-test (post-pre: $p < 0.001$; retention-pre: $p < 0.001$).

Table 1. Confusion matrix in machine learning using the SVM.

	Predicted	
	Novice	Expert
Actual novice	TP = 1310	FN = 10
Actual expert	FP = 33	TN = 107

FN, False negative; FP, False positive; TN, True negative; TP, True positive

Table 2. Feedback content.

Artificial intelligence feedback	
Satisfactory movement coordination	Sequence (pelvis-torso-left elbow) “The movements were well presented in the order of the pelvis-torso-left elbow.” Launch angle and target angle (29°)
Unsatisfactory movement coordination	1) Back swing "During the back swing, gather strength on both big toes, bend the pelvis and knees, make a back swing in a gathered state, and hit the ball instantly." 2) Front leg stride "When you fold your front leg before the stride, do not let your body lean backward and extend only as far as the tee." 3) Forward swing "Swing with your body at an angle, use your knees and hips, and keep your back elbow toward your chest." 4) Sequence (pelvis-torso-left elbow) "Rotate the pelvis first, keep the elbows in, do not stop after impact, rotate all the way thinking that the ball is far away." Launch angle and target angle (29°)
General feedback	
Satisfactory movement coordination	Professional baseball coaches’ positive knowledge of performance on movement coordination 1) Back swing 2) Front leg stride 3) Forward swing 4) Sequence (pelvis-torso-left elbow) Launch angle and target angle (29°)
Unsatisfactory movement coordination	Professional baseball coaches’ prescriptive knowledge of performance on movement coordination 1) Back swing 2) Front leg stride 3) Forward swing 4) Sequence (pelvis-torso-left elbow) Launch angle and target angle (29°)

Table 3. Motions of joints and segments used in the principal component analysis (PCA).

Joints/segments	Plane of motion	Movement
Shoulder	sagittal plane	flexion-extension
	frontal plane	adduction-abduction
	horizontal plane	horizontal adduction-horizontal abduction
Elbow	sagittal plane	flexion-extension
	horizontal plane	pronation-supination
Wrist	sagittal plane	flexion-extension
	frontal plane	adduction-abduction
Torso	horizontal plane	clockwise-counter clockwise
Hip	sagittal plane	flexion-extension
	horizontal plane	clockwise-counter clockwise
	frontal plane	adduction-abduction
Pelvis	horizontal plane	clockwise-counter clockwise
Knee	sagittal plane	flexion-extension
Ankle	sagittal plane	flexion-extension
	frontal plane	inversion-eversion
Front foot	frontal plane	medial-lateral

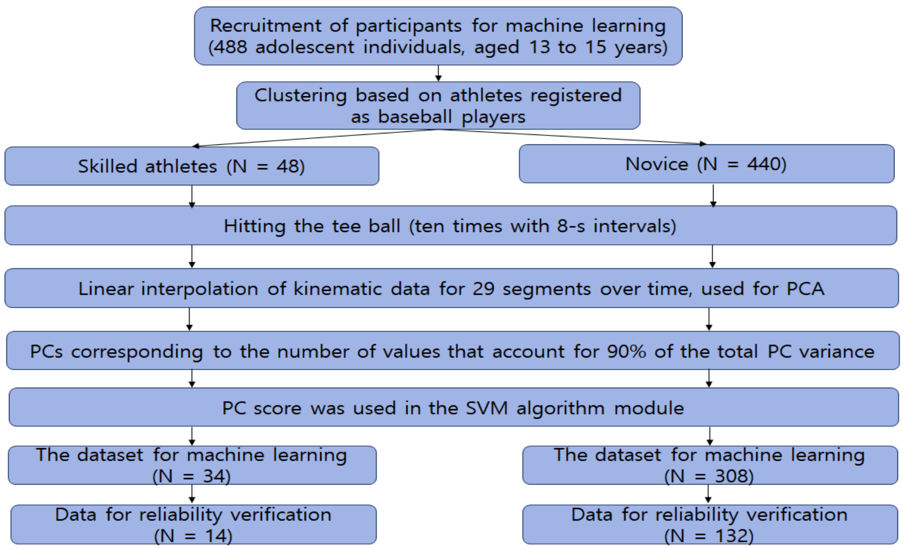

Figure 1. Diagram of the sample selection process in the machine learning experiment.

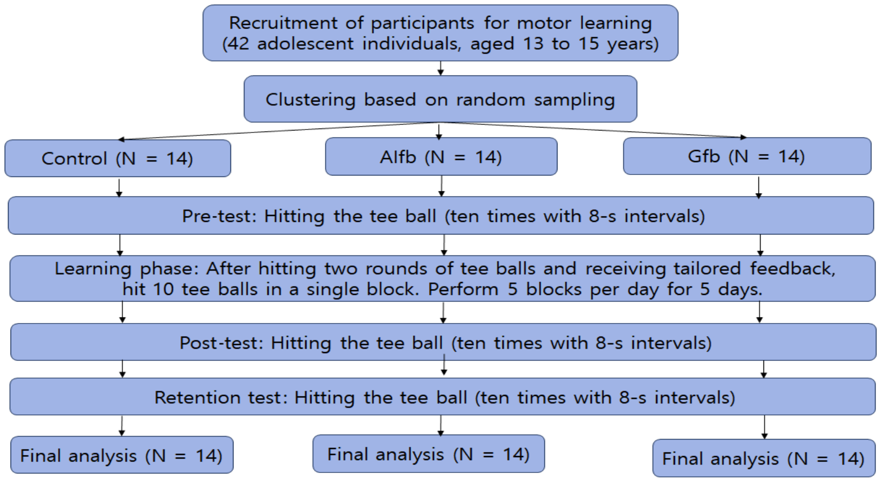

Figure 2. Diagram of the sample selection process in the motor learning experiment.
AIfb, Artificial intelligence feedback group; Gfb, general feedback group

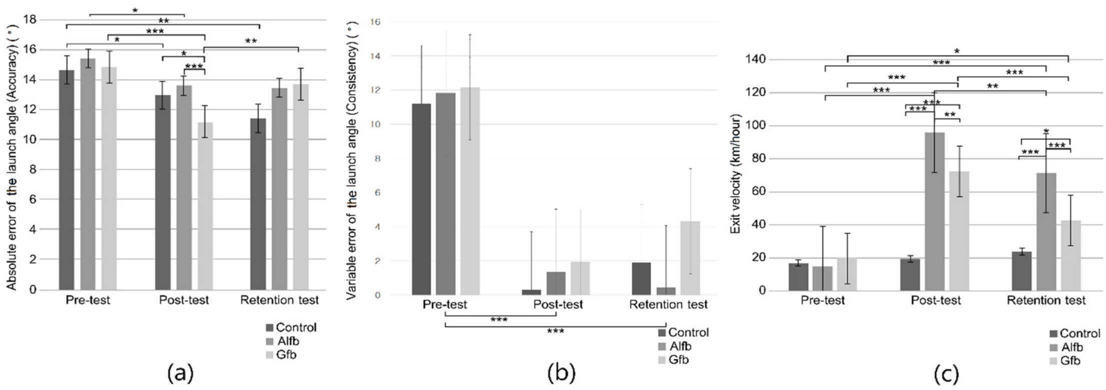

Figure 3. Motor task outcomes. (a) Absolute error (accuracy) of the launch angle, (b) variable error (consistency) of the launch angle, and (c) exit velocity according to the group and the test session.
*AIfb, Artificial intelligence feedback group; Gfb, general feedback group; * p < 0.05; ** p < 0.01; *** p < 0.001*

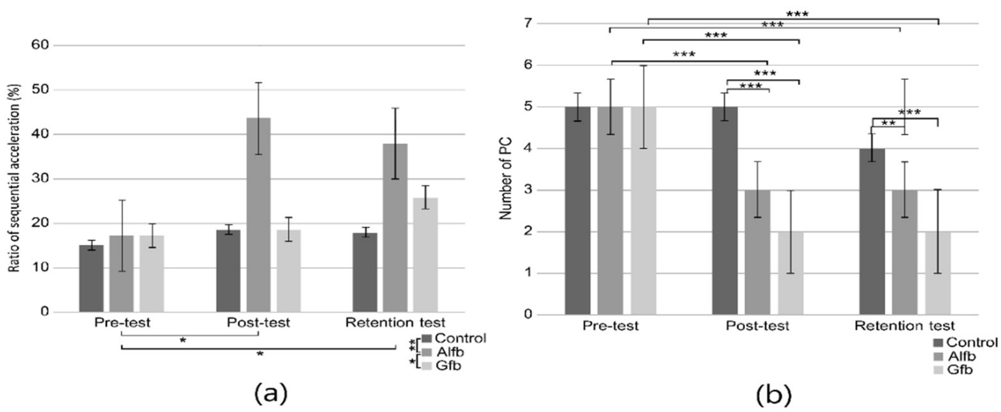

Figure 4. Movement coordination. (a) The ratio of sequential acceleration according to the group and the test session, and (b) the mode of the number of PC according to the group and the test session. ** p < 0.05; ** p < 0.01; *** p < 0.001*

Discussion

Verification of Machine Learning

In this study, we used machine learning to classify baseball players' proficiency as either expert or novice based on baseball hitting videos, achieving an F1-score of 0.98. The significance of this study lies in the automatic classification of the complex motor skill of hitting using video data (Eubank and Farmer, 1997). Experts can perform baseball hitting techniques with a smaller number of coordinated group movements than novices. However, in experts, much more joints were matched within these fewer coordination groups, resulting in more joints influencing the hitting technique compared to novices (Table S1). This was evident from the mode value of the N_{PC} with variance exceeding 90%, which was 4 for experts and 5 for novices. The roles of these joints can be found in Supporting Information Table S1, where the three joints with the highest loading values for each principal component (PC) are highlighted in dark grey, representing distinct coordination groups. We selected the top three loading data values for each principal component because they represented the most significant contributions to the variance explained by that component. By focusing on these high-loading joints, we aimed to identify the key joints that most strongly influenced the principal components, allowing us to effectively group and interpret the dynamical degrees of freedom in the context of the movements being analysed (Guo et al., 2002). By examining the three joints with the highest values in the loading data of each PC, it was found that in experts, each of the four PCs (four coordination groups) involved different joints, resulting in a total of 12 joint movements influencing the hitting technique. In contrast, for novices, the five PCs (five coordination groups) included overlapping joints, resulting in a total of 8 joint movements influencing the striking technique. This indicates that experts control their bodies more efficiently than novices. These interpretations based on principal components are not amenable to conventional statistical tests, as the highest-loading joints are unique across PCs and not repeated. Although this information does not appear in the main results section, it is explained qualitatively in the following discussion based on the loading values provided in Supporting Information Table S1.

The ulnar-radial flexion of the right wrist showed a high loading value in PC1 for experts (Table S1), but was absent in all PCs (PC1–PC5) accounting for 90% of the variance in novices, indicating its importance in differentiating between proficiency levels. In novices, the coordinated group of movements did not involve this most distal joint (wrist joint), resulting in poor performance in sequential patterns (Putnam, 1993), and this omission of the distal joint in movement was also noted in previous studies (Vereijken et al., 1992). For PC2, experts exhibited a coordinated hip movement pattern, whereas novices showed a coordination pattern involving pelvic rotation and flexion-extension of the right elbow and the left knee. This suggests that, for novices, there were no coordination groups formed by the hip joints, which means that the kinetic chain necessary for sequential acceleration of the lower limb movements to the upper limb movements was not established (Hirashima et al., 2008). For PC3, the medial-lateral movement of the left foot had a high contribution only in experts, suggesting that novices lacked the distal lower limb movements necessary to increase ground reaction forces or shift the center of gravity. Thus, it could be concluded that novices had not developed exploitation of reactive forces, which is the third stage of motor learning suggested by Bernstein (Burton and Rodgerson, 2001). The present experiment successfully classified the aforementioned features using the SVM. Beyond the automated classification of simple or slow movements, this study successfully classified a complex motor skill, such as hitting, through machine learning. This research will be essential in the current era of big data and artificial intelligence. These findings imply that experts can effectively achieve perception-action coupling, a process by which motor actions are continuously adjusted based on sensory information, allowing for fine-tuned and adaptive movement patterns in dynamic environments such as baseball hitting. In contrast, novices' lack of distal joint involvement may reflect insufficient sensory-motor integration, leading to less adaptive control.

Motor Learning and Control Experiment

The outcomes of the motor task, specifically accuracy as represented by the launch angle, mostly improved in the Gfb group at the post-test, but did not show improvements at the retention test. This suggests that, unlike other groups, the Gfb group did not effectively achieve perception-action coupling regarding the launch angle, despite receiving feedback from the coach. The Gfb group received verbal feedback from a professional baseball coach regarding their form and the launch angle. Therefore, it can be interpreted that the coach's verbal feedback was not retained within the perceptual-motor workspace, and thus failed to support launch angle adjustment during the retention test conducted after a considerable delay. This suggests that verbal feedback provided directly by a human led to a failure in facilitating perception-action coupling over the long term. Considering AIfb, an improvement in accuracy was observed in the post-test; however, as there was no significant difference compared to the control group in the post-test and the retention test, this cannot be viewed as a positive effect of the feedback. This suggests that, for novice adolescents learning the hitting technique, numerical information about the angle was not effectively integrated into action through perception (Fajen et al., 2008).

One important point to highlight regarding the consistency variable is that for Gfb, the variable error tended to increased again in the retention test compared to the post-test. This can be considered in conjunction with the previously interpreted accuracy. In other words, the Gfb group failed to maintain the perception-action coupling related to the motor task outcome in the retention test. This suggests that participants were unable to retain the quantitative information within their perceptual-motor workspace when receiving verbal feedback from the coach. What should have been memorized was not merely a motor pattern, but the perceptual-motor relationship embedded within the individual’s perceptual-motor workspace. In the context of this study, the perceptual-motor workspace referred to the internalized mapping between the intended hitting angle (29 degrees), the visual tracking of the ball’s trajectory after impact, and the feedback-based recognition of whether the actual hitting angle matched the target. This involved the integration of perceptual information and motor adjustments necessary to achieve the desired outcome. Therefore, the Gfb group’s failure to maintain performance in the retention test suggests that they did not sufficiently internalize this perceptual-motor relationship, which is essential for sustaining the perception-action coupling beyond the immediate presence of external (verbal) feedback. Overall in the motor learning process, all groups showed a decrease in variability. This suggests that participants were processing temporal and spatial aspects of movement coordination not to perceive the accuracy of the launch angle, but to achieve more consistent ball contact. In other words, novices adjusted their postural control of hitting techniques based on the temporal and spatial information obtained through motor learning, which is considered to have influenced changes in whole-body coordination and exit velocity in the hitting technique (Li, 2006). This may have been related to an increase in exit velocity and a decrease in the N_{PC} at the retention test in the feedback groups (Mitra et al., 1998). A decrease in the N_{PC} implies a decrease in the dynamical degrees of freedom in the coordinated group (Ko et al., 2013). From the perspective of the dynamical systems theory, which views motor behavior as the result of interactions among multiple components over time, a decrease in the number of sub-movements could be considered a decrease in the coordinated group, which is a phenomenon that occurs during the motor learning process (Morais et al., 2026; Tinmark et al., 2010). In motor control, sub-movements refer to smaller corrective or component motions that make up a complete action. Early in learning, these sub-movements tend to occur frequently as the performer attempts to correct for errors or instability during execution. From the perspective of the dynamical system theory, a high number of sub-movements reflects limited control over the available degrees of freedom. As learning progresses, the system becomes more efficient by organizing and constraining redundant degrees of freedom into functional synergies, leading to a reduction in sub-movements. Therefore, a decrease in sub-movements indicates an increase in motor coordination and control, where the dynamical degrees of freedom are no longer acting independently, but are effectively coupled within a coordinated group (Bernstein, 1967; Ko et al., 2013). Unlike simple reaching tasks, this study employed striking tasks, which made the participants recognize the launch angle and the exit velocity. Therefore, the decrease in the number of coordinated groups appeared to improve accuracy due to motor learning and may have improved the consistency of the launch angle (decreasing VE) in novices. The exit velocity increased significantly in the AIfb group compared with that in other groups. This result may be interpreted as a significant contribution of AIfb to the improvement of exit velocity and the higher ratio of sequential acceleration in the order of the pelvis-torso-left elbow joint during motor performance in this group. This means, the rotation of the pelvis, the torso, and the left elbow movement were more expressed as a PDS in the AIfb group, resulting in sequential acceleration and an increase in exit velocity (Santos et al., 2010).

The movement coordination was examined based on the ratio of sequential acceleration and N_{PC}. First, the ratio of sequential acceleration showed a significant improvement only in the AIfb group. This observation could suggest that the sequential acceleration of baseball hitting techniques, through motor learning, led to improved performance in the AIfb compared to the Gfb group. AIfb provides objective feedback by allowing participants to accurately understand their biomechanical movement deficiencies, whereas Gfb relies on the subjective judgment of a baseball coach to assess and provide feedback on physical movements. Therefore, it can be interpreted that improving movement coordination in a short period in novice is more difficult with Gfb. This could be considered along with the reduction in the N_{PC}. The N_{PC} significantly decreased in the AIfb and Gfb groups at the post-test and the retention test, respectively, compared with the control group. This meant that in the AIfb group, the number of coordinated groups describing baseball hitting techniques decreased from five to three, and those in the Gfb group, from five to two (Ko and Newell, 2015; Santos et al., 2010; Song et al., 2022). This can be interpreted as a result of excessively fixed degrees of freedom in the Gfb group. In this context, "excessively fixed degrees of freedom" refer to the tendency of novices in the Gfb group to overly constrain joint movements rather than developing flexible and adaptive coordination patterns. Instead of integrating multiple joints into smooth, sequential acceleration (as seen in the AIfb group), they may have simplified the movement by freezing certain joints, a strategy commonly observed in early stages of motor learning (Bernstein, 1967). While this reduces complexity, it can also limit the ability to generate optimal force and timing, thereby hindering the development of expert-like performance. With regard to the AIfb group, AIfb provides objective information about deficiencies in the learners' hitting techniques. However, in the Gfb group, psychological factors, such as the coach's prediction by repetitive motions for movements, inevitably affected the feedback. Therefore, the number of coordinated groups in the Gfb group may have been further reduced to two compared to that in the AIfb group due to the above difference. In particular, examining the joints that contributed to movement through loading data would be required; their relationship could be interpreted more specifically, depending on which parties contributed together.

Observing the loading data at the retention test, as shown in Tables S2–S4, for the AIfb group, the upper limbs, pelvis, torso, and left knee joints were included in their coordinated group, whereas for the Gfb group, only the upper limbs and pelvis joints were included. Comparing them to the experts, both groups that received feedback did not use the front leg stride or the movement of the wrist as a coordinated group. However, there were changes in the AIfb group, including the rotation of the torso for PC2; in the Gfb group, the left knee joint movement was eliminated from PC1, and only shoulder and elbow movements were included in PC2. Compared to the AIfb group, the Gfb group seemed to have separated the relatively proximal rotation of the pelvis from the relatively distal movement of the upper limbs to form a coordinated group, thereby reducing the number of coordinated groups.

Based on such changes, it can be interpreted that both the dynamical degrees of freedom interpreted as the number of coordinated groups, and the biomechanical degree of freedom interpreted as the loading data within each coordinated group, were larger and more diverse in the AIfb group than in the Gfb group at the retention test (Ko and Newell, 2015; Newell and Vaillancourt, 2001). This phenomenon may have led to a lower rate of sequential acceleration in the Gfb group than in the AIfb group, leading to a significantly smaller exit velocity in the Gfb group than in the AIfb group, because it allows for faster bat swings through sequential acceleration, which can increase the ball's exit velocity. This suggests that the Gfb group remained in the stage of freezing rather than in the stage of release of the degree of freedom relative to the AIfb group (Burton and Rodgerson, 2001).

This study demonstrates how different types of feedback influence key aspects of motor learning, particularly perception-action coupling, movement coordination, and the use of degrees of freedom. Verbal feedback from coaches was associated with improvements in certain performance aspects, such as launch angle accuracy, but showed limited effectiveness in enhancing other variables like movement coordination and exit velocity. In contrast, AI-based feedback, which provided quantifiable and objective data, supported more stable sensorimotor integration and promoted adaptive movement strategies. The AIfb group showed signs of transitioning from freezing to releasing degrees of freedom—an important step toward efficient coordination, while the Gfb group appeared to remain in a more constrained control mode. Principal component analysis further revealed that skilled performers used fewer, more efficient coordination patterns, while novices exhibited fragmented control. Machine learning classification confirmed that specific biomechanical features could reliably distinguish between expertise levels, indicating the potential of AI tools not only for feedback but also for assessment. Overall, the integration of biomechanical and learning data highlights that effective feedback fosters not just repetition, but exploration and refinement of control strategies.

Conclusions

Baseball hitting, a complex motor skill, was converted into a large amount of data. Proficiency of posture could be classified through a machine learning algorithm, and the effectiveness of AIfb was confirmed. Compared to Gfb, AIfb based on a large amount of data did not contribute to the improve accuracy and consistency of the launch angle, which was the motor task outcome of the hitting technique, but it was effective in improving the exit velocity. In addition, compared to the Gfb group, the AIfb group demonstrated a positive trend in the improvement of PDS, indicating coordination structure, which refers to the movement coordination of the hitting technique and the change in N_{PC}. This suggested the possibility of AIfb effectively changing the dynamical degrees of freedom. Therefore, AIfb created through machine learning contributed positively to the improvement of movement coordination rather than motor task outcomes, which would be of great help to coaching in a real-life setting and understanding the whole-body coordination mechanism involved in the hitting technique.

To validate the efficiency of AIfb relative to Gfb in the field, various sensory feedbacks need to be considered together, and feedback that can induce positive psychological changes in motor learning by identifying learners' motivation or task tendencies should also be established.

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Informed Consent: Informed consent was obtained from all participants included in the study.

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References

Begg, R., & Kamruzzaman, J. (2005). A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data. *Journal of Biomechanics, 38*(3), 401–408. DOI: 10.1016/j.jbiomech.2004.05.002

Bernstein, N. (1967). *The coordination and regulation of movements.* Pergamon Press.

Burton, A. W., & Rodgerson, R. W. (2001). New perspectives on the assessment of movement skills and motor abilities. *Adapted Physical Activity Quarterly, 18*(4), 347–365. DOI: 10.1123/apaq.18.4.347

Chang, J. H., Wang, C. J., Zhong, H. X., Weng, H. C., Zhou, Y. K., Ong, H. Y., & Lai, C. F. (2024). Artificial intelligence learning platform in a visual programming environment: exploring an artificial intelligence learning model. *Educational Technology Research and Development, 72*(2), 997–1024. DOI: 10.1007/s11423-023-10323-z

Chang, M., O'Dwyer, N., Adams, R., Cobley, S., Lee, K. Y., & Halaki, M. (2020). Whole-body kinematics and coordination in a complex dance sequence: Differences across skill levels. *Human Movement Science, 69*, 102564. DOI: 10.1016/j.humov.2019.102564

Conforti, I., Mileti, I., Del Prete, Z., & Palermo, E. (2020). Measuring biomechanical risk in lifting load tasks through wearable system and machine-learning approach. *Sensors, 20*(6), 1557. DOI: 10.3390/s20061557

Dounskaia, N., Goble, J. A., & Wang, W. (2011). The role of intrinsic factors in control of arm movement direction: Implications from directional preferences. *Journal of Neurophysiology, 105*(3), 999–1010. DOI: 10.1152/jn.00630.2010

Eubank, S. G., & Farmer, J. D. (1997). Probability, random processes, and the statistical description of dynamics. In L. Lam (Ed.), *Introduction to Nonlinear Physics.* (pp. 106–178). Springer Science & Business Media. DOI: 10.1007/978-1-4612-2238-5_6

Fajen, B. R., Riley, M. A., & Turvey, M. T. (2008). Information, affordances, and the control of action in sport. *International Journal of Sport Psychology, 40*(1), 79–107.

Federolf, P., Roos, L., & Nigg, B. M. (2013). Analysis of the multi-segmental postural movement strategies utilized in bipedal, tandem and one-leg stance as quantified by a principal component decomposition of marker coordinates. *Journal of Biomechanics, 46*(15), 2626–2633. DOI: 10.1016/j.jbiomech.2013.08.008

Guo, Q., Wu, W., Massart, D. L., Boucon, C., & de Jong, S. (2002). Feature selection in principal component analysis of analytical data. *Chemometrics and Intelligent Laboratory Systems, 61*(1–2), 123–132. DOI: 10.1016/S0169-7439(01)00203-9

Haywood, K. M., & Getchell, N. (2021). *Life Span Motor Development* (7th ed.). Human kinetics.

Hirashima, M., Kudo, K., Watarai, K., & Ohtsuki, T. (2007). Control of 3D limb dynamics in unconstrained overarm throws of different speeds performed by skilled baseball players. *Journal of Neurophysiology, 97*(1), 680–691. DOI: 10.1152/jn.00348.2006

Hirashima, M., Yamane, K., Nakamura, Y., & Ohtsuki, T. (2008). Kinetic chain of overarm throwing in terms of joint rotations revealed by induced acceleration analysis. *Journal of Biomechanics, 41*(13), 2874–2883. DOI: 10.1016/j.jbiomech.2008.06.014

Hong, S. L., & Newell, K. M. (2006). Change in the organization of degrees of freedom with learning. *Journal of Motor Behavior, 38*(2), 88–100. DOI: 10.3200/JMBR.38.2.88-100

Hulteen, R. M., Morgan, P. J., Barnett, L. M., Stodden, D. F., & Lubans, D. R. (2018). Development of foundational movement skills: A conceptual model for physical activity across the lifespan. *Sports Medicine, 48*, 1533–1540. DOI: 10.1007/s40279-018-0892-6

Kang, B. (2021). How the COVID-19 pandemic is reshaping the education service. In J. Lee & S. H. Han (Eds.), *The Future of Service Post–COVID–19 Pandemic* (Vol. 1, pp. 15–36). Springer. DOI: 10.1007/978-981-33-4126-5_2

Katsumata, H., Himi, K., Ino, T., Ogawa, K., & Matsumoto, T. (2017). Coordination of hitting movement revealed in baseball tee-batting. *Journal of Sports Sciences, 35*(24), 2468–2480. DOI: 10.1080/02640414.2016.1275749

Ko, J. H., Challis, J. H., & Newell, K. M. (2013). Postural coordination patterns as a function of rhythmical dynamics of the surface of support. *Experimental Brain Research*, *226*(2), 183–191. DOI: 10.1007/s00221-013-3424-5

Ko, J. H., & Newell, K. M. (2015). Organization of postural coordination patterns as a function of scaling the surface of support dynamics. *Journal of Motor Behavior, 47*(5), 415–426. DOI: 10.1080/00222895.2014.1003781

Lawrence, G. R., Gottwald, V. M., Hardy, J., & Khan, M. A. (2011). Internal and external focus of attention in a novice form sport. *Research Quarterly for Exercise and Sport, 82*(3), 431–441. DOI: 10.1080/02701367.2011.10599775

Lee, H. S., & Lee, J. (2021). Applying artificial intelligence in physical education and future perspectives. *Sustainability, 13*(1), 351. DOI: 10.3390/su13010351

Li, Z. M. (2006). Functional degrees of freedom. *Motor Control, 10*(4), 301–310. DOI: 10.1123/mcj.10.4.301

Magill, R., & Anderson, D. (2021). *Motor Learning and Control: Concepts and applications* (12th ed.). McGraw-Hill.

McErlain-Naylor, S. A., King, M. A., & Felton, P. J. (2021). A review of forward-dynamics simulation models for predicting optimal technique in maximal effort sporting movements. *Applied Sciences, 11*(4), 1450. DOI: 10.3390/app11041450

Miao, J., & Zhu, W. (2022). Precision-recall curve (PRC) classification trees. *Evolutionary Intelligence, 15*(3), 1545–1569. DOI: 10.1007/s12065-021-00565-2

Mitra, S., Amazeen, P. G., & Turvey, M. T. (1998). Intermediate motor learning as decreasing active (dynamical) degrees of freedom. *Human Movement Science, 17*(1), 17–65. DOI: 10.1016/S0167-9457(97)00023-7

Morais, C. Z., Bispo, J. C. D. S., Ueda, L. S. C., Milistetd, M., da Silva, J. F. & Borges, P. H. (2026). The Role of Instructional Constraints Performed by Coaches on Tactical Behavior of Soccer Players: A Systematic Review. *Journal of Human Kinetics*, *100*, 293–308. https://doi.org/10.5114/jhk/202057

Müller, S., & Abernethy, B. (2012). Expert anticipatory skill in striking sports: A review and a model. *Research Quarterly for Exercise and Sport, 83*(2), 175–187. DOI: 10.1080/02701367.2012.10599848

Nalepa, J., & Kawulok, M. (2019). Selecting training sets for support vector machines: a review. *Artificial Intelligence Review, 52*(2), 857–900. DOI: 10.1007/s10462-017-9611-1

Newell, K. M., & Vaillancourt, D. E. (2001). Dimensional change in motor learning. *Human Movement Science, 20*(4–5), 695–715. DOI: 10.1016/s0167-9457(01)00073-2

Newell, K. M. (1991). Motor skill acquisition. *Annual Review of Psychology, 42*, 213–237. DOI: 10.1146/annurev.ps.42.020191.001241

Noble, W. S. (2006). What is a support vector machine? *Nature Biotechnology*, *24*(12), 1565–1567. DOI: 10.1038/nbt1206-1565

Oh, S., & Kim, D. K. (2019). Development of Squat Posture Guidance System Using Kinect and Wii Balance Board. *Journal of Information and Communication Convergence Engineering, 17*(1), 74–83. DOI: 10.6109/jicce.2019.17.1.74

Ong, N. T., & Hodges, N. J. (2020). Motor learning. In D. Hackfort & R. J. Schinke (Eds.), *The Routledge International Encyclopedia of Sport and Exercise Psychology* (pp. 356–374). Routledge. DOI: 10.4324/9781315187259

Oppici, L., Dix, A., & Narciss, S. (2021). When is knowledge of performance (KP) superior to knowledge of results (KR) in promoting motor skill learning? A systematic review. *International Review of Sport and Exercise Psychology, 17*(1), 182–207. DOI: 10.1080/1750984X.2021.1986849

Power, D. J. (2014). Using "Big Data" for analytics and decision support. *Journal of Decision Systems, 23*(2), 222–228. DOI: 10.1080/12460125.2014.888848

Putnam, C. A. (1993). Sequential motions of body segments in striking and throwing skills: Descriptions and explanations. *Journal of Biomechanics, 26*(Suppl. 1), 125–135. DOI: 10.1016/0021-9290(93)90084-r

Rana, M., & Mittal, V. (2020). Wearable sensors for real-time kinematics analysis in sports: A review. *IEEE Sensors Journal, 21*(2), 1187–1207. DOI: 10.1109/JSEN.2020.3019016

Sabic, E., & Chen, J. (2016). Threshold of spearcon recognition for auditory menus. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 60*(1), 1539–1543. DOI: 10.1177/1541931213601353

Santos, M. J., Kanekar, N., & Aruin, A. S. (2010). The role of anticipatory postural adjustments in compensatory control of posture: 2. Biomechanical analysis. *Journal of Electromyography and Kinesiology, 20*(3), 398–405. DOI: 10.1016/j.jelekin.2010.01.002

Schmidt, R. A. (1991). Frequent augmented feedback can degrade learning: Evidence and interpretations. In *Tutorials in Motor Neuroscience* (pp. 59–75). Springer Netherlands. DOI: 10.1007/978-94-011-3626-6_6

Sigrist, R., Rauter, G., Riener, R., & Wolf, P. (2013). Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychonomic Bulletin & Review, 20*, 21–53. DOI: 10.3758/s13423-012-0333-8

Song, Y. H., Cho, S. N., & Nam, S. M. (2022). Asymmetric influence of dual-task interference on anticipatory postural adjustments in one-leg stance. *International Journal of Environmental Research and Public Health, 19*(18), 11289. DOI: 10.3390/ijerph191811289

Tinmark, F., Hellström, J., Halvorsen, K., & Thorstensson, A. (2010). Elite golfers' kinematic sequence in full-swing and partial-swing shots. *Sports Biomechanics, 9*(4), 236–244. DOI: 10.1080/14763141.2010.535842

Uddin, M. S., Islam, S. S., & Hussain, M. M. (2022). Estimating Energy Expenditure of Push-Up Exercise in Real Time Using Machine Learning. In *International Conference on Machine Intelligence and Emerging Technologies* (pp. 674–686). Springer Nature Switzerland. DOI:10.1007/978-3-031-34622-4_53

Varea, V., & González-Calvo, G. (2021). Touchless classes and absent bodies: Teaching physical education in times of COVID-19. S*port, Education and Society, 26*(8), 831–845. DOI: 10.1080/13573322.2020.1791814

Vereijken, B., van Emmerik, R. E. A., Whiting, H. T. A., & Newell, K. M. (1992). Free(z)ing degrees of freedom in skill acquisition. *Journal of Motor Behavior, 24*(1), 133–142. DOI: 10.1080/00222895.1992.9941608

Xia, Z., Sun, D., Qian, Y., Xu, Y., Zhu, C., Cen, X., Song, Y., Xiang, L., Jemni, M. & Gu, Y. (2026). Biomechanical Strategies for Minimizing Force Plate Targeting Effects during Running: Efficacy of Masked Force Plate Integration with Augmented Visual Feedback. *Journal of Human Kinetics,* Advance online publication. https://doi.org/10.5114/jhk/212382

Yadav, S. K., Tiwari, K., Pandey, H. M., & Akbar, S. A. (2021). A review of multimodal human activity recognition with special emphasis on classification, applications, challenges and future directions. *Knowledge-Based Systems, 223*, 106970. DOI: 10.1016/j.knosys.2021.106970

Yuan, X. (2021). The application prospects of artificial intelligence in the field of physical education. In *World Automation Congress* (pp. 283–286). DOI: 10.23919/WAC50355.2021.9559508