

# Analysis of sports skill transfer and learning curves based on motor behavior data mining

*Wenxiang Long*

*Taraz International University, Taraz, Kazakhstan*

*longwenxiang02448@outlook.com*

---

**Abstract.** Sports skill transfer is difficult to evaluate through coaching observation alone because transfer appears as a gradual change in timing, force regulation, action stability, and error recurrence. This study develops a motor behavior data mining framework for analyzing transfer and learning curves across basketball free throw, volleyball overhand serve, and handball standing throw. A six-week experiment was performed on sixty students attending university physical education courses that generated a total of 36,000 attempts in training and 5,400 attempts in the pretest. This research project used action sequences, technical score, success result, error designation, and behavior logs all together in one unified dataset. The obtained results confirm a positive transfer between basketball free throw and volleyball serve skills with the transfer coefficient of  $0.46 \pm 0.18^*$ , and between volleyball serve and handball throw with the transfer coefficient of  $0.39 \pm 0.16^*$ . The technical scores increased from  $2.23 \pm 0.31$  to  $3.71 \pm 0.38$ , and the number of repeated release timing errors fell from  $3.71 \pm 0.38$  to  $1.84 \pm 0.42$  per 50 attempts.

**Keywords:** sports skill transfer, motor behavior data mining, learning curve, action sequence, skill acquisition

---

## 1. Introduction

The learning of motor skills in sport is considered a cumulative process, where prior experience influences the speed, stability, and direction of future acquisitions. As a rule, in coaching, learners do not learn a single skill but several skills. Thus, basketball free throws can help with arm and wrist alignment, while volleyball overhand serves can be useful in terms of improving body sequencing and release. There is a necessity to compare skill learning with different practice conditions in sport-related tasks because there are no unified measures of task complexity, skill learning, and testing methods for the transfer of learning [1]. Successful practice depends on challenge level, quality of repetitions, task specificity, and individual differences in learning [2].

Transfer may occur when a number of sport skills have partially similar structure. Positive transfer takes place when coordination patterns accelerate the learning process, while negative transfer is characterized by rhythm or habitual force hindering the task at hand. The meta-analysis of the problem demonstrates that the order of practice does have an influence on transfer in applied settings, but the effect is smaller and less consistent compared to lab-based tasks [3]. Thus, transfer has to be studied with behavioral data gathered over many sessions.

These data will allow us to observe such evidence. Modern motor learning theory proves that large behavioral databases can show the presence of nonlinear relations between the amount of training and transfer results [4]. From the practical point of view, routine training records can be turned into interpretable measures like sequence stability, recurring combinations of errors, slope of the curve, plateau moment, and learner groupings. Moreover, field experiments on practice prove that organismic, task and environmental constraints affect the process of solution search [5]. Sport technologies with wearable and video tracking provide opportunities to quantify the performance changes in real-world settings [6]. That is why, in this research, motor behavior data mining will be applied to examine upper-limb skill transfer and learning curves for six weeks of training.

## **2. Literature review**

### **2.1. Sports skill transfer**

Sports skill transfer is defined as the effect created by an already learned motion on the following motion. For the tasks utilizing the upper body, transfer is usually connected to postural set-up, trunk-arm coordination, timing of release, and directional control. The positive transfer appears when a learner reuses a stable element of a compatible task, whereas the negative one happens when an antecedent habit carries over to the new task with the different spatial/temporal characteristics. The latest experimental data favor viewing transfer as a behavioral relationship that can be measured rather than a general assumption based on similarity only [7].

### **2.2. Learning curves in motor skill acquisition**

Learning curve describes the development of performance during repeated practice. During the early sessions, the learner usually shows fast growth because of the clarification of the goal and reduction of overt errors. In the later sessions, improvements are slower due to smaller changes in the timing, rhythm, and accuracy that require fine control. The individual differences play a significant role because the initial high level of performance might indicate further levels of performance, and the course of learning is usually unpredictable [8]. Therefore, all elements of the learning curve must be modeled together.

### **2.3. Motor behavior data in sports training**

The motor behavior data includes action phases, results of attempts, error labeling, feedback history, self-assessment, and frequency of training. They are valuable because they come from repeated practice in reality and allow linking technical quality to the learning process. According to the recent sport-specific reviews, many motor learning researches continue using simplified tasks or novices [9]. Moreover, the sensor-based motion analysis suggests that the motion data from reality can be used for personal assessment with proper processing and validation [10].

## **3. Methods**

### **3.1. Participants, skill tasks, and training setting**

In the experiment 60 university students studying Physical Education were recruited and had an average age of 19.72 years ( $SD = 1.14$ ). These individuals have never undergone any kind of systematic training for free throws in basketball, overhand serves in volleyball, or standing throw in handball in the previous year. All these skills were selected due to their similar characteristics in the terms of upper limb propulsion, trunk

action, terminal release, and control of accuracy while being dissimilar in the terms of the target form and force direction. The training process took six weeks, including two sessions per week lasting 90 minutes each.

### 3.2. Data collection and variable design

Action sequence data were collected with fixed-position video recording at 60 frames per second. The camera was placed five meters in front of the learner and 30 degrees to the dominant-arm side to capture preparation, force generation, arm swing, release, and follow-through. Kinovea 0.9.5 marked each phase, which was coded as stable, delayed, insufficient, or excessive. Two coaches scored posture control, movement rhythm, force direction, release timing, and final accuracy on a five-point scale. Inter-rater reliability reached ICC = 0.87. Training logs recorded successful attempts, repeated error labels, feedback content, self-rated difficulty, and confidence. Variables included success rate, technical score, release-timing error frequency, sequence entropy, transfer coefficient, and plateau point.

### 3.3. Data mining and learning curve modeling

Data processing was conducted in Python 3.11, SPSS 29, and Excel. Raw video codes and logs were matched by participant ID, skill type, session number, and attempt order. Missing values caused by occluded frames were removed only when the release phase could not be identified; the final deletion rate was 2.31%. Continuous variables were standardized within each skill. Categorical action sequences were converted into five-phase strings, such as S-S-D-I-S, where each letter represented the phase-level technical state. Sequence similarity was calculated using normalized Levenshtein distance to compare whether stable components in one skill reappeared in the next skill.

The first core index was the transfer coefficient. For learner  $i$ , source skill  $a$ , and target skill  $b$ , transfer was defined as shown in Equation (1):

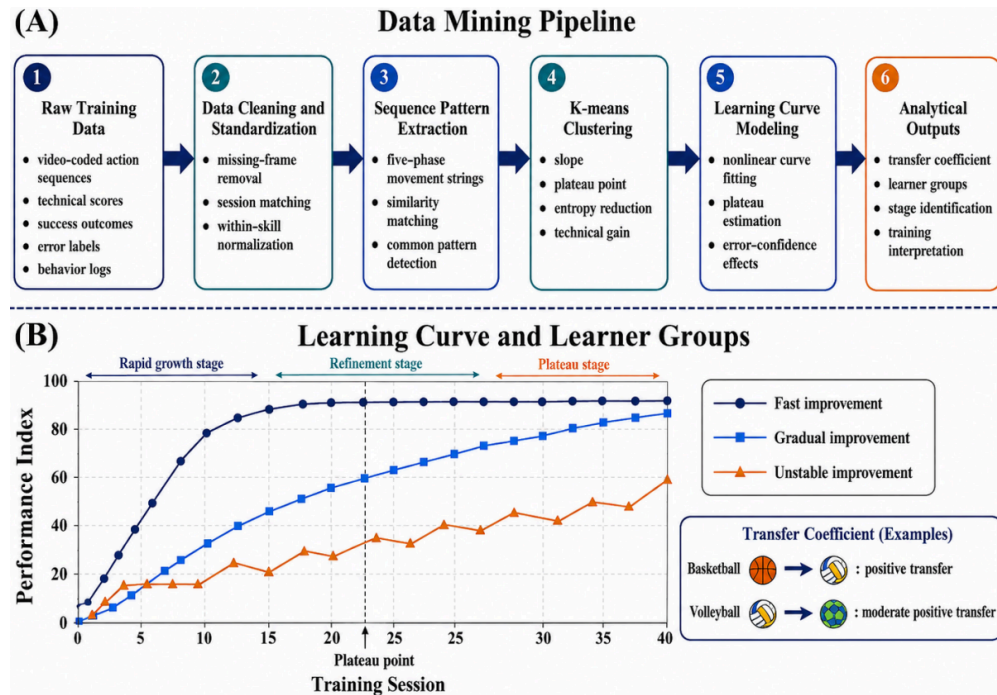
$$T_{i,a \rightarrow b} = \frac{\sum_{t=1}^m \omega_t [\Delta Q_{i,b,t} - \overline{\Delta Q_{b,t}}^{\text{base}}]}{\sqrt{\sum_{t=1}^m \omega_t (\Delta Q_{i,a,t})^2} \sqrt{\sum_{t=1}^m \omega_t (\Delta Q_{i,b,t})^2 + \varepsilon}} - \gamma D(S_{i,a}, S_{i,b}) \quad (1)$$

where  $\Delta Q$  is technical-score improvement,  $\omega_t$  is the phase weight,  $D(S_{i,a}, S_{i,b})$  is normalized sequence distance,  $\gamma$  is the penalty for incompatible carryover, and  $\varepsilon$  prevents zero-division. The second model estimated the learning curve as shown in Equation (2):

$$\hat{P}_{i,s,k} = \beta_{0i} + \frac{\beta_{1s}}{1 + \exp[-\beta_{2s}(k - \tau_{is})]} - \beta_{3s} E_{i,s,k} + \beta_{4s} C_{i,s,k} + \mu_i + \eta_s + \epsilon_{i,s,k} \quad (2)$$

where  $\hat{P}_{i,s,k}$  is predicted success rate,  $\tau_{is}$  is plateau point,  $E$  is repeated error frequency,  $C$  is confidence score,  $\mu_i$  is the individual random effect, and  $\eta_s$  is the skill fixed effect.  $K$ -means clustering used standardized slope, plateau point, entropy reduction, and technical gain. The best solution was  $K = 3$ , representing fast, gradual, and unstable improvement groups.

To illustrate the integration process of motor behavior data mining and learning curve analysis, Figure 1 presents the complete analytical framework, including data preprocessing, sequence pattern extraction, learner clustering, nonlinear curve modeling, and transfer-related outcome interpretation.



**Figure 1.** Framework of data mining pipeline and learning curve modeling for upper-limb sports skill transfer

#### 4.1. Pre-test and initial skill assessment

Before training, each subject performed 30 free throw shots in basketball, 30 serves in volleyball, and 30 throws in handball. In the pretest phase, there were 5,400 attempts, with baseline data collected on success rate, technical score, and primary error committed. The mean technical score of the subjects prior to training was  $2.23 \pm 0.31$ , which suggests basic knowledge on how to move, with a poor level of stability at the time of release.

#### 4.2. Training intervention and behavior log recording

Each training session involved a consistent procedure: 15 minutes of warming up and instructions, 60 minutes of repetition practice, and 15 minutes of feedback, reflection, and log completion. The practice attempts involved a series of five blocks of 10 repetitions each. After each block, the coach provided one feedback statement regarding the most common error, allowing for the log to link the feedback to the next 10 attempts.

The error labels were specific to each task but related to the same upper-limb control schema. The labels for basketball free throw tasks included instability in lower limb support, early arm extension, inadequate wrist flexion, and incorrect release direction. In volleyball serve tasks, the error labels were instability in toss height, late swing initiation, inadequate trunk involvement, and instability in contact point. For handball throw tasks, the error labels were insufficient trunk rotation, short arm swing, early release, and inaccurate direction control. Each error was documented relative to the attempt block, phase location, and number of recurrences. A recurrent error was defined as the same label that occurred no less than three times in the same ten-attempt block, thus making the variable sensitive to persistent technical challenges. Confidence and difficulty were also logged on a five-point scale. These were the process variables that helped explain the different trajectories of learners' performance despite similar technical scores.

### 4.3. Transfer analysis and stage identification

Transfer analysis compared source-skill improvement with early-session improvement in the target skill. Basketball-to-volleyball transfer linked the final two basketball sessions with the first two volleyball sessions. Volleyball-to-handball transfer was evaluated in the same way. The model checked whether shared movement components, especially preparation stability, trunk-arm sequencing, and release timing, were preserved or distorted. Faster stabilization of target-skill timing was coded as positive transfer, while wrist-dominant carryover causing weak trunk participation was coded as partial interference.

Learning stages were identified through curve slope and error persistence. A rapid growth stage was marked when the success-rate slope exceeded 0.045 per session and the technical score increased by at least 0.30 across two consecutive sessions. A refinement stage was marked when the success-rate slope fell below 0.030 but sequence entropy and repeated error frequency continued to decline. A plateau stage was marked when the success-rate change remained within  $\pm 0.015$  for two consecutive sessions while at least one technical error category persisted. The final interpretation combined curve parameters, error recurrence, and coach-coded phases.

## 5. Experimental results

### 5.1. Skill transfer patterns among three upper-limb tasks

The transfer analysis showed measurable positive transfer. Basketball-to-volleyball transfer was stronger because the free throw and overhand serve both required controlled upward force direction and terminal wrist coordination. The mean basketball-to-volleyball transfer coefficient was  $0.46 \pm 0.18^*$ , while the volleyball-to-handball coefficient was  $0.39 \pm 0.16^*$  (see Table 1). Negative transfer appeared mainly in learners who retained wrist-dominant force production in handball, with an interference index of  $0.17 \pm 0.06^*$ .

**Table 1.** Main experimental results across three upper-limb skill tasks

| Indicator                                   | Basketball free throw  | Volleyball overhand serve | Handball standing throw |
|---------------------------------------------|------------------------|---------------------------|-------------------------|
| Pre-test technical score                    | $2.38 \pm 0.42$        | $2.12 \pm 0.39$           | $2.19 \pm 0.37$         |
| Post-training technical score               | $3.86 \pm 0.44^{***}$  | $3.63 \pm 0.41^{***}$     | $3.58 \pm 0.46^{***}$   |
| Success rate change                         | $+0.27 \pm 0.09^{***}$ | $+0.24 \pm 0.08^{***}$    | $+0.21 \pm 0.10^{***}$  |
| Release-timing error change per 50 attempts | $-1.96 \pm 0.38^{***}$ | $-1.72 \pm 0.44^{***}$    | $-1.58 \pm 0.49^{**}$   |
| Sequence entropy change                     | $-0.43 \pm 0.11^{***}$ | $-0.38 \pm 0.10^{***}$    | $-0.34 \pm 0.12^{**}$   |
| Transfer-related early gain                 | $0.31 \pm 0.12^*$      | $0.28 \pm 0.10^*$         | $0.22 \pm 0.09^*$       |
| Estimated plateau session                   | $3.41 \pm 0.62$        | $3.76 \pm 0.71$           | $4.08 \pm 0.83$         |

Note: \*  $p < 0.05$ ; \*\*  $p < 0.01$ ; \*\*\*  $p < 0.001$ .

### 5.2. Learning curve characteristics across training sessions

Learning curves showed a nonlinear pattern. The average success-rate slope was  $0.071 \pm 0.018$  during the first two sessions of each skill, but declined to  $0.026 \pm 0.011$  after the fourth session. The model fitted the data well, with RMSE = 0.047 and conditional  $R^2 = 0.81$ . Basketball reached the plateau earliest at  $3.41 \pm 0.62$  sessions, followed by volleyball at  $3.76 \pm 0.71$  and handball at  $4.08 \pm 0.83$ .

### 5.3. Learner group differences in skill development paths

Cluster analysis identified three learner groups. The fast improvement group included 22 learners and showed the largest technical gain,  $1.72 \pm 0.36^{***}$ , with the lowest final sequence entropy,  $0.61 \pm 0.15$ . The gradual improvement group included 25 learners and showed steady gains,  $1.38 \pm 0.29^{**}$ . The unstable group included 13 learners and showed larger curve fluctuation,  $0.094 \pm 0.021^*$ . Baseline technical score was related to final performance,  $r = 0.52$ ,  $p < 0.001$ , but not strongly related to learning slope,  $r = 0.18$ ,  $p = 0.167$ .

## 6. Conclusion

This study expanded the motor behavior data mining framework into an empirical analysis of sports skill transfer and learning curves. By integrating action sequences, technical scores, success outcomes, repeated error labels, and training logs, the study showed that skill transfer among basketball free throw, volleyball overhand serve, and handball standing throw can be measured through observable indicators. Results indicated positive transfer in upper-limb timing and release control, especially from basketball free throw to volleyball serve. Learning curves showed early growth, slower refinement, and task-specific plateau stages. The main contribution is an interpretable analytical procedure that connects data mining with practical coaching judgment. Future research can extend the framework to open skills and multimodal sensor data.

## References

- [1] Choo, L., Novak, A., Impellizzeri, F. M., Porter, C., & Fransen, J. (2024). Skill acquisition interventions for the learning of sports-related skills: A scoping review of randomised controlled trials. *Psychology of Sport and Exercise*, 72, 102615.
- [2] Williams, A. M., & Hodges, N. J. (2023). Effective practice and instruction: A skill acquisition framework for excellence. *Journal of Sports Sciences*, 41(9), 833–849.
- [3] Czyż, S. H., Wójcik, A. M., & Solarská, P. (2024). The effect of contextual interference on transfer in motor learning: A systematic review and meta-analysis. *Frontiers in Psychology*, 15, 1377122.
- [4] Schoenfeld, M. J., Thom, J., Williams, J., Stagg, C. J., & Zich, C. (2024). Relationship between skill training and skill transfer through the example of bimanual motor learning. *European Journal of Neuroscience*, 59(1), 54–68.
- [5] Pacheco, M. M., de Oliveira, L. M. M., dos Santos, C. C. A., Godoi Filho, J. R. M., & Drews, R. (2023). Challenging traditions: Systematic review of practice, instruction, and motor skill acquisition in soccer. *International Journal of Sports Science & Coaching*, 18(5), 1702–1725.
- [6] Seçkin, A. Ç., Ateş, B., & Seçkin, M. (2023). Review on wearable technology in sports: Concepts, challenges and opportunities. *Applied Sciences*, 13(18), 10399.
- [7] Reis, F. J. J., Alaiti, R. K., Vallio, C. S., & Hespanhol, L. (2024). Artificial intelligence and machine learning approaches in sports: Concepts, applications, challenges, and future perspectives. *Brazilian Journal of Physical Therapy*, 28(3), 101083.
- [8] Abeles, D., Herszage, J., Shahar, M., & Censor, N. (2023). Initial motor skill performance predicts future performance, but not learning. *Scientific Reports*, 13, 11359.
- [9] Barzyk, P. B., & Gruber, M. (2024). Motor learning in golf: A systematic review. *Frontiers in Sports and Active Living*, 6, 1324615.
- [10] Arzehgar, A., Seyedhasani, S. N., Ahmadi, F. B., Baravati, F. B., Hesar, A. S., Kachooei, A. R., & Aalaei, S. (2025). Sensor-based technologies for motion analysis in sports injuries: A scoping review. *BMC Sports Science, Medicine and Rehabilitation*, 17, 15.