

## Subjective effort modulates muscle synergy recruitment during the table tennis Forehand Topspin Stroke

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Published online: February 28, 2026

Accepted for publication: February 15, 2026

DOI:10.7752/jpes.2026.02032

### Abstract:

Human voluntary movements are produced through the coordinated activation of multiple muscles, often organized by the central nervous system into functional units known as muscle synergies. Although muscle synergies are regarded as stable and efficient control structures, it remains unclear how they adapt when performers intentionally modulate subjective effort during skilled sport-specific movements. This study examined how stepwise manipulations of subjective effort influence muscle coordination during the table tennis forehand topspin stroke, a technique requiring both high power and accurate control. Ten skilled table tennis players performed forehand topspin strokes under five effort conditions (60–100%), during which surface electromyographic signals were recorded, and muscle synergies were extracted using non-negative matrix factorization. Ball speed, ball spin, and muscle activity amplitude increased progressively with higher effort levels, confirming that participants successfully adjusted output intensity in accordance with the instructed effort. In contrast, the number of extracted muscle synergies remained constant across all effort conditions, indicating that the fundamental coordination structure was preserved despite changes in subjective effort. Clustering and scalar product analyses demonstrated that, although basic synergies were shared across effort levels, supplementary synergies were selectively recruited under high-effort conditions. These supplementary synergies became more distinct as effort increased, reflecting phase-specific adjustments in muscle contributions to meet greater output demands and support local stabilization. The high structural similarity of synergy patterns across effort levels further confirmed that skilled performers maintained stable coordination patterns regardless of effort magnitude. Overall, these findings suggest that increases in subjective effort do not reorganize muscle coordination patterns; rather, they are achieved through intensity scaling of basic synergies accompanied by the selective recruitment of supplementary synergies. This study provides new insight into effort-dependent modulation of neuromuscular coordination in a complex racket sport skill and offers a foundation for effort-based training strategies that preserve coordination stability while enhancing output control.

**Keywords:** motor control, effort modulation, surface electromyography, muscle synergies, non-negative matrix factorization, racket sports

### Introduction

Human voluntary movements are produced through the coordinated activation of numerous muscles. Rather than controlling the vast degrees of freedom of individual muscles independently, the central nervous system is thought to organize functionally related muscles into “muscle synergies,” adjusting their activation intensity and timing to efficiently generate movement. Muscle synergies are considered a simplification strategy that enables the central nervous system to integrate and control multiple muscles efficiently. They have been consistently observed across diverse movements, such as reaching and walking (Ivanenko et al., 2004; d’Avella et al., 2006). Muscle synergy analysis, which decomposes surface electromyography (sEMG) signals using non-negative matrix factorization (NMF) to extract muscle weighting vectors (W) and temporal activation patterns (C), has become a widely used method for quantitatively investigating the mechanisms of motor control (Hug, 2011; Frère & Hug, 2012; Hagio & Kouzaki, 2014; Vaz et al., 2016).

Muscle synergy analysis has also been applied in sports science. Previous studies have determined the number of synergies based on Variance Accounted For (VAF) and compared synergy structures using correlation coefficients or scalar products (SP) to examine how muscle coordination patterns vary with task characteristics or skill level. In relatively simple motor tasks, such as rowing or the bench press, similar numbers of synergies have been reported for elite and non-elite performers (Turpin et al., 2011; Kristiansen et al., 2015). Applications of muscle synergy analysis have also begun to emerge in racket sports (Matsunaga & Kaneoka, 2018; Wang et al., 2025). For example, in the badminton overhead smash, the movement can be explained by

three synergies regardless of skill level (Barnabehei et al., 2018). These findings suggest that, regardless of skill level, efficient movement patterns may be acquired through sport-specific practice and movement experience. At the same time, muscle synergies are not fixed modules. Previous research has demonstrated their plasticity, including changes in the number of synergies and adjustments in muscle weightings depending on skill level or task constraints (Kibushi, 2024). Thus, motor skills likely involve both task-invariant coordination patterns and condition-dependent patterns that are flexibly adjusted according to task demands.

Table tennis requires not only tactical insight but also advanced cognitive and motor preparation (Bańkosz & Winiarski, 2018). Players must make precise judgments and execute controlled movements within extremely short time frames. Under such temporal and technical constraints, athletes employ various strategies to gain a competitive advantage. A primary example is imparting spin to the ball. Spin alters flight trajectory and constrains an opponent's response options, making the ability to generate high levels of spin strategically essential (Zagatto et al., 2018). Reflecting these demands, many elite players adopt an offensive playing style (Wang et al., 2018). The forehand topspin stroke is the most frequently used offensive technique (Seemiller & Holowchak, 1997).

This stroke relies on efficient energy transfer from the trunk to the upper limb, contributing to increased racket speed (Iino & Kojima, 2011), which in turn enhances ball velocity and spin. Accordingly, the forehand topspin stroke represents a key determinant of performance with direct implications for competitive outcomes. Supporting such high-power and precise movements requires coordinated control among multiple muscles in addition to sufficient strength. Research on muscle activity in table tennis has a long history. Ogimura (1973) was the first to systematically classify the muscle groups involved in table tennis strokes, identifying the biceps brachii, deltoid, pectoralis major, and abdominal muscles as key contributors. Following this early work, quantitative evaluations using sEMG have been conducted to investigate the muscles involved in table tennis techniques. Previous studies have reported activation patterns in major upper-limb muscles, such as the pectoralis major, deltoid, biceps brachii, and forearm muscles (Kondrič et al., 2006; Tsai et al., 2010; Maheshwari et al., 2022, 2023). They have also identified muscle activity in the trunk and lower limbs (Le Mansec et al., 2018). However, these studies focused primarily on the activity levels of individual muscles. To date, no study has examined table tennis strokes within a muscle synergy framework that captures coordinated relationships among multiple muscles.

In table tennis, athletes frequently adjust force distribution and timing based on subjective effort, and this internal sense may play a significant role in movement control. Variations in coordination patterns associated with changes in effort have been reported in other skilled domains, such as music and sports (Hashimoto et al., 2021). For example, in piano performance, increasing effort makes performer-specific movement characteristics more pronounced (Furuya et al., 2012), suggesting that changes in effort can influence muscle coordination patterns. Previous research (Sato et al., 2025) has shown that higher subjective effort increases ball speed and spin while reducing perceived control and increasing perceived strain. These findings indicate that fluctuations in effort affect not only output intensity but may also impact aspects of muscle coordination. However, the manner in which subjective effort alters coordination patterns remains unclear. Specifically, it is unknown whether coordination patterns are reorganized or whether existing synergies simply adapt through intensity scaling or condition-dependent adjustments. Thus, a central unresolved issue is whether intentional effort modulation changes synergy structure or primarily modulates recruitment within a preserved synergy framework. Clarifying this issue is essential for understanding how effort modulation affects coordination in skilled performance and for informing evidence-based coaching strategies. Such insight may contribute to more effective skill acquisition and provide guidance on appropriate force application in table tennis.

The purpose of this study was to clarify how stepwise manipulations of subjective effort (60–100%) alter muscle coordination patterns during the table tennis forehand topspin stroke. An additional aim was to identify the characteristics of coordination patterns associated with changes in effort and to explore their potential applications for motor skill learning. Accordingly, we used multi-muscle surface electromyography during forehand topspin strokes performed at graded, subjectively controlled effort levels to determine whether effort modulation alters coordination structure or mainly scales activation within a preserved framework. Clarifying how subjective effort modulation shapes multi-muscle coordination may provide a physiological basis for optimizing effort regulation and coordination strategies in training and competition.

## Methods

### *Participants*

Ten male collegiate table tennis players with experience competing in national-level tournaments participated in this study. All were right-handed. Their mean  $\pm$  SD age, height, and body mass were  $20.6 \pm 1.6$  years,  $169.4 \pm 6.0$  cm, and  $61.1 \pm 6.5$  kg, respectively. None reported any orthopedic disorders or upper-limb injuries. The study protocol was approved by the Ethics Committee of Niigata University (approval number: 2023-0236). Before participation, all individuals received a detailed explanation of the study objectives and procedures and provided written informed consent.

### Experimental Task

After completing a standardized warm-up, participants performed forehand topspin strokes. Balls delivered to the forehand side were returned toward the diagonal target area of the opponent's court. The following instruction was provided: "Assume that 100% represents your maximal-effort stroke. Please perform a forehand topspin stroke toward the diagonal court at an effort level of X%." Five subjective effort levels were tested: 60%, 70%, 80%, 90%, and 100%. The trial order was fixed as 80%, 60%, 90%, 70%, and 100%. This ordering was used to avoid anchoring 100% as a reference point and to reduce referential bias by preventing consecutive trials with adjacent effort levels (Sato et al., 2025). For each effort level, one stroke that the participant judged as matching the instructed effort level was selected for analysis. Ball feeding was performed by a certified Japan Table Tennis Association coach who was highly experienced and left-handed. Participants used their own rackets, all of which were offensive models equipped with high-tension inverted rubbers (maximum sponge thickness). The mean racket mass was  $186.6 \pm 4.1$  g.

### Measurements

Surface electromyography (sEMG) was recorded from ten right-side muscles: biceps brachii (BB), triceps brachii lateral head (TBLa), triceps brachii long head (TBLo), pectoralis major (PM), deltoid anterior (DA), deltoid posterior (DP), flexor carpi radialis (FCR), extensor carpi radialis (ECR), rectus abdominis (RA), and trapezius (TRA). Wireless EMG sensors (LP-WS1221, LP-WS1223; Logical Product, Japan) recorded signals at a sampling frequency of 1000 Hz with a gain of 1000. Electrode placement followed the SENIAM recommendations (Hermens et al., 2000). The skin was shaved and cleaned with alcohol prior to electrode placement. EMG signals were filtered using a fourth-order Butterworth digital band-pass filter (20–450 Hz) before further analysis.

Ball speed was recorded at 240 fps using digital cameras positioned in front of and lateral to the participant (EX-ZR70; CASIO, Japan). The recordings were analyzed using three-dimensional motion analysis software (Frame DIAS V; DKH Inc., Japan), and coordinates were calculated using the Direct Linear Transformation method. The ball center was manually digitized frame by frame. Optimal cutoff frequencies for each coordinate axis were determined using residual analysis, and the coordinate data were smoothed with a Butterworth low-pass filter using the calculated cutoff values (6–12 Hz) (Winter, 1990). Ball speed (km/h) was calculated using the central difference method applied to the three frames immediately following ball–racket separation. Ball spin (rps) was recorded at 600 fps using a high-speed camera positioned laterally (EX-F1; CASIO, Japan). A circular black marker was drawn on the ball surface with an oil-based pen to track rotation. After ball–racket separation, the number of frames required for the marker to complete three full rotations was counted manually, and spin rate was calculated from this value.

### Data analysis

Table tennis strokes consist of three phases: the preparation phase, the main action phase, and the follow-through phase (Kondrič et al., 2006). In this study, these were defined as the backswing phase, forward-swing phase, and follow-through phase. A marker was placed on the racket head, and its three-dimensional coordinates were captured and analyzed using motion analysis software (Frame DIAS V; DKH Inc., Japan). The coordinate system was defined with the positive X-axis directed anteriorly, the positive Y-axis to the left, and the positive Z-axis vertically upward relative to the participant. Stroke cycles were segmented into four key time points (T1–T4) based on racket-head kinematics. T1 (movement onset) was defined as the moment when the racket-head X-coordinate began to decrease from the ready position, indicating the onset of backward motion, and when racket-head velocity exceeded 2.0 m/s for the first time. T2 (end of backswing) was defined as the transition point from the preparation phase to the main action phase, identified by a change in racket-head tangential acceleration from negative to positive. T3 (impact) corresponded to the moment of ball–racket contact, identified using high-speed video. T4 (end of follow-through) was defined as the point at which the follow-through motion was completed and racket-head tangential acceleration returned to zero. To standardize the temporal scale of the stroke cycle, the duration between T1 and T4 was time-normalized, with T1 set to 0% and T4 set to 100%. After normalization, the transition from T1 to T2 occurred on average at approximately 60% of the stroke cycle, and T3 (impact) occurred at approximately 75%. Based on these definitions, the movement between T1 and T4 was divided into three phases: T1–T2 as the backswing phase, T2–T3 as the forward-swing phase, and T3–T4 as the follow-through phase (Figure 1). The interval from T1 to T4 was treated as one complete stroke, and EMG data corresponding to this interval were extracted for analysis.

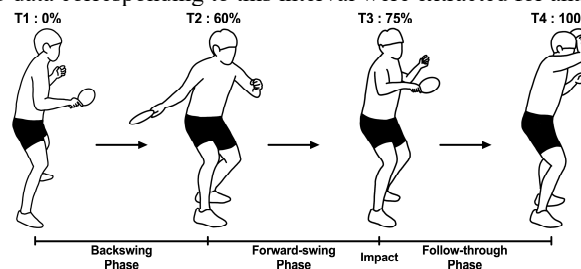


Fig.1. Definition of swing phases (T1–T4).

After filtering, the EMG signals were full-wave rectified and smoothed using a zero-phase, second-order Butterworth low-pass filter with a cutoff frequency of 7 Hz. Each stroke was resampled to 101 data points to normalize the timescale. For each muscle, the smoothed EMG signals were further normalized to the maximum muscle activation obtained across all effort-level conditions within the same participant (Yokoyama et al., 2016). Muscle synergy analysis was performed using non-negative matrix factorization (NMF) to extract muscle coordination modules (Lee & Seung, 2001). NMF decomposes a given matrix into the product of two non-negative matrices, as shown in Equation (1):

$$E = WC + e \quad (1)$$

The EMG matrix  $E$  was defined as a  $p \times n$  matrix ( $p$ : number of muscles,  $n$ : number of time points), which in this study consisted of 10 muscles and 101 time-normalized points. The matrix  $W$  was a  $p \times s$  matrix ( $s$ : number of extracted synergies) representing the muscle weighting vectors (i.e., the contribution of each muscle to each synergy). The matrix  $C$  was an  $s \times n$  matrix representing the temporal activation patterns of the extracted synergies. The residual matrix  $e$  was a  $p \times n$  matrix representing the reconstruction error. For each participant, NMF was performed while varying the number of synergies from 1 to 10. The optimal number of synergies was determined based on the Variance Accounted For (VAF). Specifically, the smallest number of synergies that satisfied both a global VAF  $\geq 90\%$  (Hagio & Kouzaki, 2014) and a local VAF  $\geq 75\%$  (Hug, 2010) was selected. VAF quantifies the extent to which the product of  $W$  and  $C$  reconstructs the original EMG signals. Global VAF evaluates the reconstruction error across all muscles and indicates the overall fidelity with which the extracted synergies represent the original EMG data. It is defined by Equation (2):

$$\text{Global VAF} = \left( 1 - \frac{\sum_{i=1}^p \sum_{j=1}^n (e_{i,j})^2}{\sum_{i=1}^p \sum_{j=1}^n (E_{i,j})^2} \right) \times 100(\%) \quad (2)$$

In contrast, the local VAF evaluates the reconstruction error for each individual muscle and reflects the reconstruction accuracy of specific muscles. It is defined by Equation (3):

$$\text{Local VAF} = \left( 1 - \frac{\sum_{j=1}^n (e_{m,j})^2}{\sum_{j=1}^n (E_{m,j})^2} \right) \times 100(\%) \quad (3)$$

In Equation (3),  $m$  indicates each individual muscle. Global VAF was used to evaluate the overall reconstruction accuracy of the extracted synergies, whereas local VAF was used to assess the reconstruction accuracy for each muscle. To evaluate the similarity of muscle synergies extracted from each participant, hierarchical clustering (Ward's method, Euclidean distance) was applied to the muscle weighting vectors ( $W$ ) (Yokoyama et al., 2016; Delis et al., 2018). The number of clusters was automatically determined using the Gap statistic (Tibshirani et al., 2001). As a result of the clustering, multiple  $W$  vectors from the same participant and the same effort condition were sometimes classified into the same cluster. In such cases, the scalar product (SP) was used as an index to evaluate the similarity between each  $W$  and the cluster center (i.e., the mean vector within the cluster) (Cheung et al., 2012). SP quantifies the structural similarity between two muscle weighting vectors and is defined as shown in Equation (4), representing the inner product of the two vectors normalized by their respective norms.

$$\text{SP}(W_i, W_j) = \frac{\overline{W}_i \cdot \overline{W}_j}{\|\overline{W}_i\| \|\overline{W}_j\|} \quad (4)$$

In this analysis,  $\overline{W}_i$  and  $\overline{W}_j$  denote the two muscle weighting vectors being compared, and  $\|\overline{W}_i\|$  and  $\|\overline{W}_j\|$  represent their respective norms. An SP value closer to 1 indicates a higher similarity between the corresponding muscle synergy structures. When multiple  $W$  vectors from the same participant and the same effort condition were included in the same cluster, the  $W$  with the highest SP relative to the cluster center was selected as the single representative vector, and the remaining overlapping vectors were excluded. Furthermore, to verify the consistency within each cluster, the mean SP between the cluster center and each  $W$  (i.e., the within-cluster mean SP) was calculated to assess the similarity within the cluster (Scano et al., 2019). Next, to determine the correspondence of muscle synergy structures across effort conditions, SP values were computed between cluster centers ( $W$ ) for each effort level, and matching was performed based on similarity. Clusters obtained under the 100% effort condition were used as the reference. SP values between the reference clusters and clusters from other effort levels were then calculated to define correspondence. When multiple matching candidates existed for a single cluster, correspondences were assigned in descending order of SP. In addition, the temporal activation patterns ( $C$ ) corresponding to each  $W$  were averaged, and these averaged waveforms were used to compare the temporal characteristics of the synergies across effort conditions.

#### Statistical analysis

Differences in the number of muscle synergies, ball speed, and ball spin across effort conditions were examined. The Shapiro–Wilk test was used to assess normality, and Levene's test was used to evaluate homogeneity of variance. When both assumptions were satisfied, one-way analysis of variance was performed, followed by Tukey's post hoc test. When either assumption was violated, the Friedman test was applied, and

Dunn's post hoc test was used for multiple comparisons. All analyses were conducted using Prism 10 (GraphPad Software, USA), and the significance level was set at 5% ( $p < 0.05$ ).

## Results

Figure 2 illustrates the mean ball speed and ball spin across effort conditions. Ball speed (km/h) increased significantly with higher effort levels ( $\chi^2 (5) = 39.28$ ,  $p < 0.001$ ). The mean values were  $59.2 \pm 3.4$  km/h at 60%,  $63.0 \pm 3.2$  km/h at 70%,  $65.8 \pm 3.8$  km/h at 80%,  $69.7 \pm 2.9$  km/h at 90%, and  $75.9 \pm 3.2$  km/h at 100%. Dunn's post hoc test revealed significant differences between 60% and 80%, 60% and 90%, 60% and 100%, and 70% and 100%. Ball spin (rps) also differed significantly across effort levels ( $\chi^2 (5) = 34.51$ ,  $p < 0.001$ ). The mean values were  $105.5 \pm 5.2$  rps at 60%,  $112.7 \pm 4.7$  rps at 70%,  $115.6 \pm 5.1$  rps at 80%,  $118.6 \pm 5.0$  rps at 90%, and  $124.3 \pm 4.5$  rps at 100%. Dunn's post hoc test indicated significant differences between 60% and 90%, 60% and 100%, 70% and 100%, and 80% and 100%.

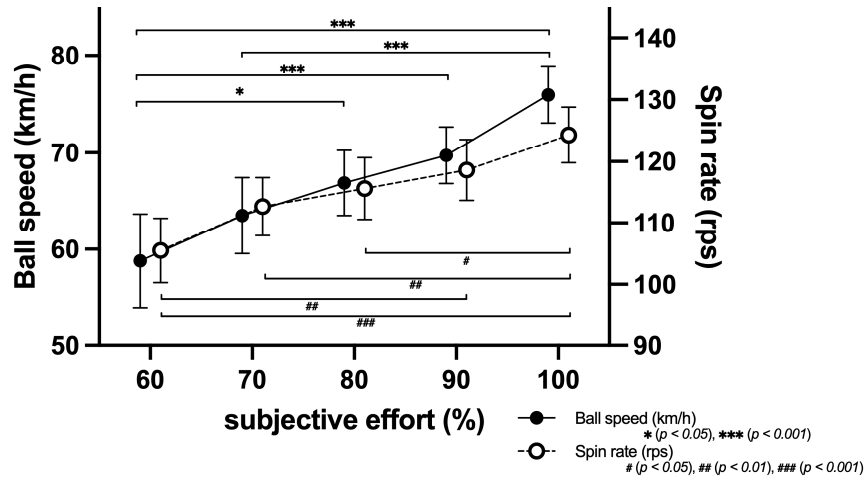


Fig.2. Ball speed and ball spin across effort levels.

Figure 3 presents the mean EMG waveforms during the forehand topspin stroke for each effort level. In many muscles, EMG amplitude tended to increase with higher effort levels.

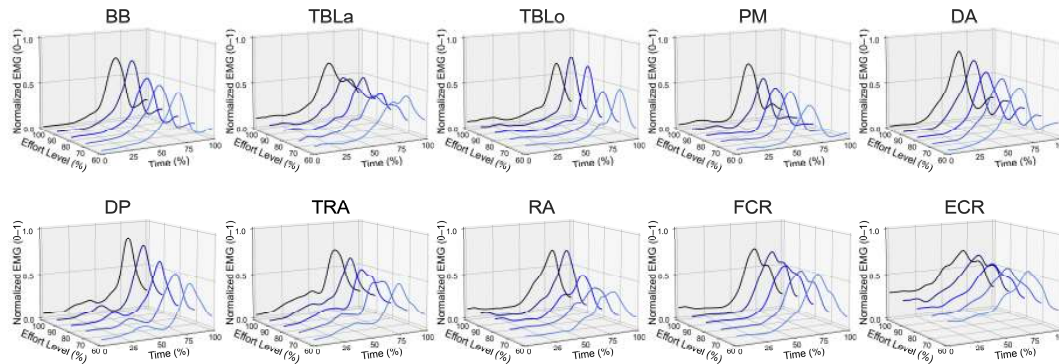


Fig.3. Mean EMG waveforms across effort levels.

Table 1 shows the changes in VAF values according to the number of extracted synergies for each effort condition. At all effort levels, both global VAF and local VAF increased as the number of synergies increased. The smallest number of synergies satisfying the predefined criteria (global VAF  $> 0.90$  and local VAF  $> 0.75$ ) was selected as optimal for each condition. Across effort levels (60–100%), the minimum synergy number (s) was most frequently 2 or 3, with occasional occurrences of 4.

Table 1. Changes in VAF values across synergy numbers for each effort level.

| s  | 60%             |                 | 70%             |                 | 80%             |                 | 90%             |                 | 100%            |                 |
|----|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|    | Global VAF      | Local VAF       | Global VAF      | Local VAF       | Global VAF      | Local VAF       | Global VAF      | Local VAF       | Global VAF      | Local VAF       |
| 1  | $0.78 \pm 0.04$ | $0.44 \pm 0.09$ | $0.79 \pm 0.03$ | $0.40 \pm 0.09$ | $0.78 \pm 0.03$ | $0.40 \pm 0.10$ | $0.78 \pm 0.04$ | $0.45 \pm 0.10$ | $0.78 \pm 0.04$ | $0.44 \pm 0.13$ |
| 2  | $0.91 \pm 0.02$ | $0.70 \pm 0.10$ | $0.91 \pm 0.02$ | $0.74 \pm 0.09$ | $0.91 \pm 0.02$ | $0.73 \pm 0.09$ | $0.91 \pm 0.02$ | $0.77 \pm 0.06$ | $0.90 \pm 0.02$ | $0.73 \pm 0.07$ |
| 3  | $0.96 \pm 0.01$ | $0.84 \pm 0.05$ | $0.96 \pm 0.01$ | $0.84 \pm 0.05$ | $0.96 \pm 0.01$ | $0.87 \pm 0.04$ | $0.95 \pm 0.01$ | $0.86 \pm 0.03$ | $0.95 \pm 0.01$ | $0.85 \pm 0.07$ |
| 4  | $0.98 \pm 0.01$ | $0.90 \pm 0.05$ | $0.98 \pm 0.01$ | $0.92 \pm 0.03$ | $0.98 \pm 0.00$ | $0.92 \pm 0.03$ | $0.98 \pm 0.01$ | $0.91 \pm 0.05$ | $0.98 \pm 0.01$ | $0.93 \pm 0.03$ |
| 5  | $0.99 \pm 0.00$ | $0.93 \pm 0.05$ | $0.99 \pm 0.00$ | $0.95 \pm 0.02$ | $0.99 \pm 0.00$ | $0.96 \pm 0.01$ | $0.99 \pm 0.00$ | $0.95 \pm 0.05$ | $0.99 \pm 0.00$ | $0.96 \pm 0.01$ |
| 6  | $1.00 \pm 0.00$ | $0.97 \pm 0.03$ | $1.00 \pm 0.00$ | $0.97 \pm 0.02$ | $1.00 \pm 0.00$ | $0.98 \pm 0.01$ | $1.00 \pm 0.00$ | $0.98 \pm 0.01$ | $0.99 \pm 0.00$ | $0.98 \pm 0.01$ |
| 7  | $1.00 \pm 0.00$ | $0.99 \pm 0.01$ | $1.00 \pm 0.00$ | $0.98 \pm 0.02$ | $1.00 \pm 0.00$ | $0.99 \pm 0.01$ | $1.00 \pm 0.00$ | $0.99 \pm 0.01$ | $1.00 \pm 0.00$ | $0.99 \pm 0.00$ |
| 8  | $1.00 \pm 0.00$ | $0.99 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $0.99 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ |
| 9  | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ |
| 10 | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ | $1.00 \pm 0.00$ |

(Mean  $\pm$  S.D.)

Figure 4 shows the number of synergies extracted at each effort level. The mean number of synergies was  $2.7 \pm 0.5$  at 60%,  $2.7 \pm 0.5$  at 70%,  $2.6 \pm 0.5$  at 80%,  $2.5 \pm 0.5$  at 90%, and  $2.9 \pm 0.6$  at 100%. No significant differences were observed across effort conditions ( $\chi^2(5) = 4.89$ ,  $p = 0.299$ ).

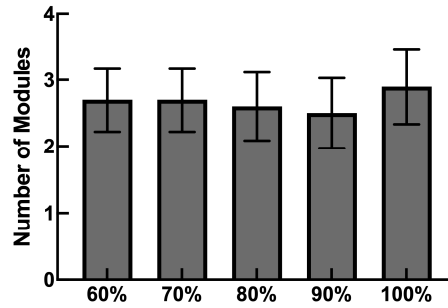


Fig.4. Number of synergies extracted at each effort level.

Figure 5 presents the optimal number of clusters determined using the Gap statistic. The optimal cluster numbers were 2 at 60% effort, 4 at 70%, 3 at 80%, 4 at 90%, and 5 at 100%. These values were used for clustering the muscle synergies at each effort level, followed by similarity evaluation and cross-effort matching.

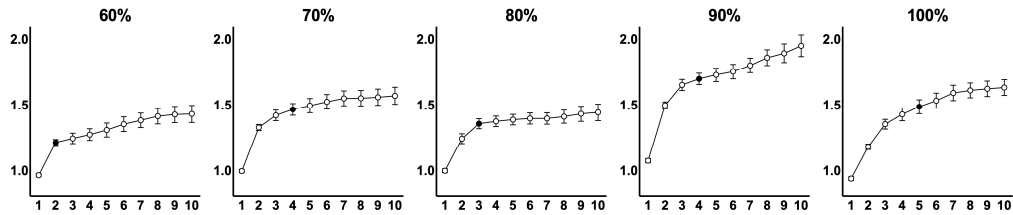


Fig.5. Optimal number of clusters determined using the Gap statistic.

Figure 6 shows the mean within-cluster SP values obtained after hierarchical clustering. For all clusters, the mean SP was 0.75 or higher, indicating consistent muscle synergy structures within clusters.

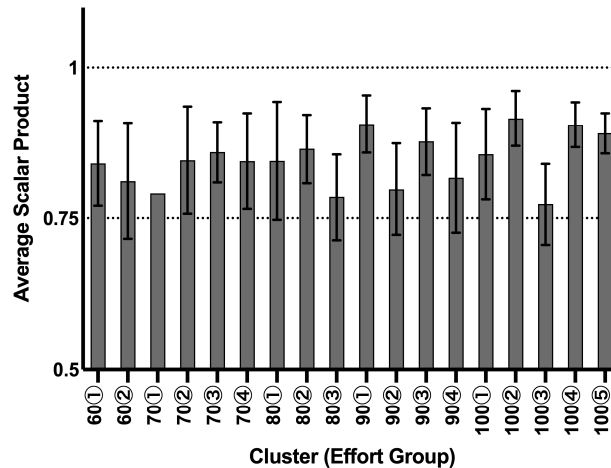


Fig.6. Mean within-cluster SP values across all clusters.

Table 2 presents SP values between the five cluster centers identified under the 100% effort condition and the corresponding cluster centers from the other effort conditions. Pairs with  $SP \geq 0.75$  were defined as “same synergies,” and matching across effort levels was performed based on this criterion. All matched pairs exhibited SP values exceeding 0.90. Clusters 1 and 2 at 100% effort had corresponding clusters at all other effort levels. Cluster 3 corresponded to clusters at 70% and 80%, Cluster 4 to clusters at 70% and 90%, and Cluster 5 to clusters at 90%.

Table 2. SP values for cross-effort matching based on the 100% effort clusters.

|     |   | 60   |      | 70   |      |      |      | 80   |      |      | 90   |      |      |      |
|-----|---|------|------|------|------|------|------|------|------|------|------|------|------|------|
|     |   | 1    | 2    | 1    | 2    | 3    | 4    | 1    | 2    | 3    | 1    | 2    | 3    | 4    |
| 100 | 1 | 0.54 | 0.99 | 0.46 | 0.99 | 0.56 | 0.54 | 0.99 | 0.58 | 0.74 | 0.99 | 0.58 | 0.62 | 0.51 |
|     | 2 | 0.96 | 0.60 | 0.44 | 0.59 | 0.73 | 0.98 | 0.54 | 0.98 | 0.78 | 0.56 | 0.64 | 0.98 | 0.84 |
|     | 3 | 0.69 | 0.74 | 0.91 | 0.72 | 0.57 | 0.71 | 0.65 | 0.67 | 0.95 | 0.70 | 0.72 | 0.79 | 0.74 |
|     | 4 | 0.74 | 0.66 | 0.70 | 0.68 | 0.99 | 0.66 | 0.62 | 0.76 | 0.65 | 0.59 | 0.95 | 0.75 | 0.41 |
|     | 5 | 0.83 | 0.46 | 0.52 | 0.45 | 0.41 | 0.91 | 0.41 | 0.80 | 0.79 | 0.46 | 0.43 | 0.83 | 0.98 |

Figure 7 illustrates the activation patterns of each synergy across effort levels. With increasing effort, synergy 3 was observed at 70%, 80%, and 100%; synergy 4 at 70%, 90%, and 100%; and synergy 5 at 90% and 100%. Figure 7A presents the muscle weighting vectors ( $W$ ) for synergies classified as identical across effort levels, and Figure 7B shows the corresponding temporal activation patterns ( $C$ ). The  $W$  patterns of each synergy exhibited similar muscle compositions regardless of the effort level.

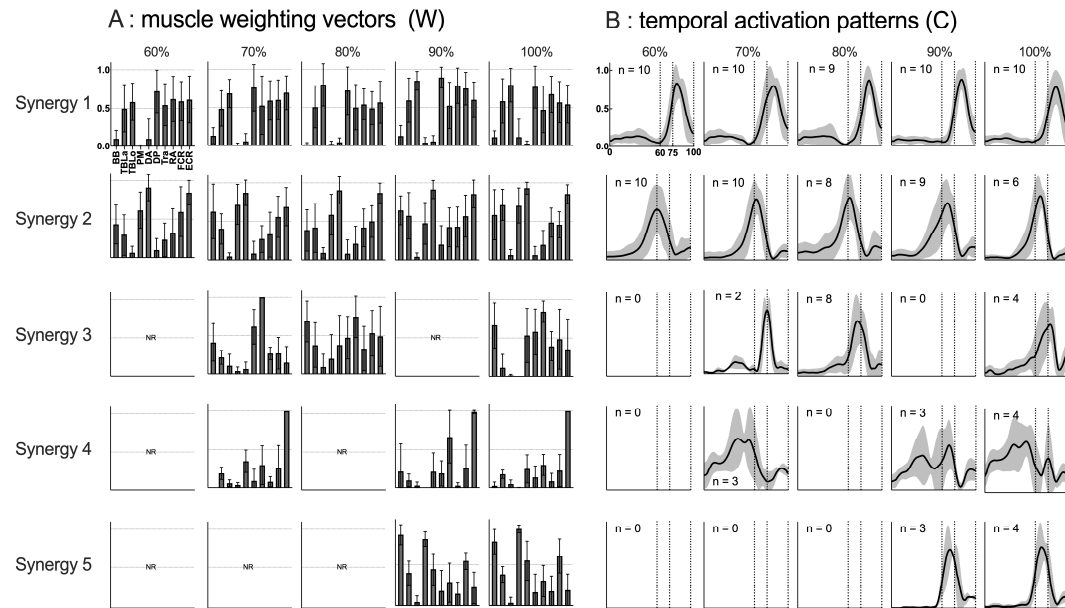


Fig.7. Module activation patterns across effort levels (A: muscle weighting vectors  $W$ ; B: temporal activation patterns  $C$ ).

## Discussion

This study examined how stepwise manipulations of subjective effort during the table tennis forehand topspin stroke are reflected in muscle coordination patterns. Ball speed and ball spin increased progressively with effort, indicating that participants generated outputs consistent with the instructed levels. These findings align with those of previous studies showing that higher subjective effort corresponds to greater objective performance (Sato et al., 2025). This supports the validity of the effort manipulation used in the present study. Normalized EMG amplitudes also increased in many muscles as effort rose, suggesting that higher subjective effort was expressed as greater relative muscle activation. Clear stepwise increases were observed in the biceps brachii, pectoralis major, anterior deltoid, posterior deltoid, and rectus abdominis, muscles that play central roles in upper-limb and trunk motion. They contribute to racket acceleration and movement stability through shoulder and trunk rotation (Tsai et al., 2010). The amplitude increases observed in these muscles indicate that the effort manipulation was performed appropriately. They also suggest that muscle activity may have been scaled proportionally in response to changes in subjective effort.

In contrast, the minimum number of muscle synergies extracted by NMF was concentrated around three for most participants across the 60–100% effort range. No statistical differences in synergy number were observed across effort conditions. Both global and local VAF met the required criteria for all conditions. These results suggest that the fundamental units of coordination remained unchanged even as subjective effort increased, indicating a stable control structure within individuals. Given that the interpretation of synergy number should depend on task characteristics (Kibushi, 2024), the present findings imply that increasing effort in the forehand topspin stroke does not generate entirely new coordination patterns. Rather, performance output appears to be regulated by modulating the contribution of existing synergies (Tresch et al., 2006). This interpretation aligns with previous reports that skilled movements maintain a consistent number of synergies (Hug et al., 2010). In highly practiced actions, stable control is likely achieved through a limited set of synergies. Although individual differences were observed in this study, with synergy numbers ranging from two to four, the overall structure converged toward a similar pattern across participants. Research considering expertise has further suggested that skilled performers may exhibit supplementary synergies in addition to basic shared synergies (Kim et al., 2017). Because the present study examined highly trained athletes, it is plausible that the neuromuscular system regulated output by scaling existing synergies rather than reorganizing coordination patterns in response to different effort levels. Thus, effort manipulation did not increase coordination complexity. Instead, it functioned as an output-scaling mechanism that recruited the same synergies at different intensities.

At the individual level, synergy number remained constant. However, when synergies from all participants were pooled and subjected to cluster analysis, greater diversity in cluster structure emerged at higher effort levels. In the high-effort condition, five optimal clusters were identified, indicating increased variability in

muscle coordination patterns at the group level. This pattern likely reflects adjustments in specific muscle contributions in response to greater output demands, superimposed on common basic synergies. These changes in cluster structure do not indicate the formation of entirely new coordination patterns; rather, they suggest the presence of supplementary synergies recruited alongside the basic synergies, resulting in a more subdivided appearance of coordination patterns. Thus, increased effort did not alter the fundamental structure of coordination but was expressed as adjustments in muscle contributions within existing synergies and the selective recruitment of supplementary synergies. Furthermore, evaluation of the correspondence across effort conditions using scalar products between cluster centers showed that all scalar product values exceeded 0.90 when the 100% effort condition was used as the reference. Two clusters (Synergy 1 and Synergy 2) showed correspondence across all effort levels. This high level of agreement indicates that the primary muscle combinations did not change substantially with increasing effort and that the basic coordination patterns continued to function stably even under high-effort conditions. Previous studies have reported that upper-limb muscles exhibit common activation phases across stroke types (Tsai et al., 2010). The present study quantitatively demonstrated this characteristic from the perspective of muscle synergies. Therefore, subjective effort did not greatly modify the basic coordination patterns—that is, “which muscles are used and in what proportion.” Instead, effort primarily acted on the aspect of intensity adjustment, namely “how strongly the existing muscle activities are recruited.”

When examining the function of muscle synergies along the time course of movement, Synergy 4 was activated first during the backswing phase. This synergy exhibited dominant ECR activity, which likely contributed to stabilization around the wrist joint. The forehand stroke involves a countermovement sequence in which the engaged muscles are first stretched and then shortened during the forward-swing phase to accelerate the body and upper limb (Lees, 2003). This sequence facilitates elastic energy storage and stretch-reflex enhancement, enabling maximal muscle recruitment within a short period (Komi, 1984). Therefore, the body and racket motions during the backswing phase have a substantial influence on the topspin stroke. Previous studies have reported that, in the early phase of the forehand stroke, it is important to establish favorable mechanical conditions at both the shoulder and wrist joints (Tsai et al., 2010). Other studies have indicated that optimizing joint angles and muscle length during the preparation phase is essential (Kondrič et al., 2006). Based on these findings, the activation of Synergy 4 in the present study likely functioned as a preparatory synergy that facilitated such preparatory control. In other words, Synergy 4 can be interpreted as a synergy that stabilizes the distal segments of the upper limb while optimizing conditions for the forward swing. During the main action phase, the center of mass shifts from the rear to the front (Mao et al., 2023), and a kinetic chain is activated, transmitting force from the lower limbs to the upper limbs (Kondrič et al., 2006). Synergy 2 played a primary role from the backswing phase to the early portion of the forward-swing phase. This synergy was characterized by coordinated activity centered on the PM, DA, and ECR, with moderate contributions from the BB, TBLA, and FCR. These muscles have been reported to contribute to upper-limb acceleration during the forehand stroke (Tsai et al., 2010; Maheshwari et al., 2022). Therefore, the muscle composition of Synergy 2 observed in this study is consistent with the characteristics of the major muscle groups that contribute to propulsion in the early forward-swing phase. Following this, from the latter half of the forward-swing phase to just before impact, Synergy 5 appeared to be recruited in a supplementary manner. This synergy was characterized by force generation primarily involving the PM and BB, which likely contributed to the additional acceleration immediately before impact. At the same time, activity of the FCR increased, contributing to stabilization of the racket face by ensuring sufficient wrist stiffness. This finding is consistent with previous reports indicating that coordinated contractions of the forearm flexors and the BB play a key role in stabilizing the racket face during the forehand stroke (Tsai et al., 2010; Kondrič et al., 2006). These results suggest that skilled players can maintain swing precision even under high-effort conditions. At the moment of impact, Synergy 3 was activated, with notable contributions from the DP and TRA. These muscles have been reported to play a role in stabilizing the scapular region and maintaining posture at impact (Tsai et al., 2010). The activity of Synergy 3 observed in this study likely reflects a brief adjustment that stabilizes the upper limb in accordance with the timing of ball–racket contact. During the follow-through phase, Synergy 1 was activated, with particularly strong contributions from the TBLA and the DP. Moderate contributions from the TBLA, TRA, RA, FCR, and ECR were also observed. The activation of these muscles likely contributed to the deceleration of the upper limb immediately after impact and to the stabilization of the scapular region and trunk, thereby supporting postural recovery following ball contact. The follow-through motion is positioned as an extension of the forward-swing phase, and movements in this phase have been reported to indirectly reflect the overall stability of the stroke (Lees, 2003). In addition, the follow-through is known to facilitate a smooth transition to the subsequent movement (Kondrič et al., 2006). The muscle composition of Synergy 1 observed in this study is therefore considered appropriate for a synergy responsible for deceleration control and postural maintenance after impact. It can also be interpreted as contributing to the overall stability of the forehand topspin stroke. Viewed holistically, Synergy 1 (deceleration and stabilization) and Synergy 2 (acceleration) were consistently present across all effort levels, indicating their role as fundamental coordination synergies. In contrast, Synergies 3–5 were more frequently recruited under higher effort conditions, functioning as supplementary modules that provided phase-specific stabilization or additional acceleration. Their activation patterns were consistent with the increase in output observed as the

effort levels increased. Notably, some supplementary synergies were not extracted under submaximal conditions. This reflects the fact that these synergies were not basic synergies but supplementary elements recruited only in specific phases of the movement. Under submaximal effort conditions, the contribution of these supplementary synergies was relatively small, and their activity did not exhibit patterns sufficiently independent of the primary synergies. Consequently, they were less likely to be extracted as separate synergies under certain conditions. In contrast, at high effort levels, the increased output demands likely caused the activity of supplementary synergies to become more pronounced. This pronounced activity made them easier to identify as distinct coordination patterns. In other words, the increase in output associated with higher effort levels cannot be explained solely by the intensity scaling of basic synergies. This was also achieved through the phase-specific recruitment of supplementary synergies, such as the selective activation of Synergies 3 and 5 and the preparatory contribution of Synergy 4 during the forward-swing phase. The condition-dependent nature of these supplementary synergies aligns with previous findings. Specifically, earlier research has shown that increases in walking speed lead to changes in synergy recruitment and activation patterns, and that higher output demands can destabilize synergy activity (Kibushi, 2024). Therefore, higher subjective effort in the forehand topspin stroke appears to be accommodated by preserving basic coordination patterns while supplementing them at critical phases.

In summary, the findings of this study suggest that increases in subjective effort did not reorganize the coordination patterns themselves. Instead, participants adapted to greater output demands by adjusting muscle contributions while maintaining the basic synergies. They also selectively recruited supplementary synergies when required in specific phases. The clearer emergence of supplementary synergies under high-effort conditions suggests that the neuromuscular system may engage additional stabilization and fine-tuning mechanisms to maintain movement integrity under demanding conditions. From a practical standpoint, training that systematically varies effort levels may enhance output flexibility while preserving coordination stability, potentially improving phase-specific performance elements such as pre-impact stabilization and late-phase acceleration. However, a limitation of this study is that only upper-limb muscles were examined, making it difficult to fully assess the kinetic chain involving the lower limbs and trunk. Moreover, research on muscle synergies in table tennis remains limited; therefore, the present interpretations should be considered within the scope of the current design. Future investigations should incorporate whole-body muscle recordings and examine adaptive responses under varying skill levels and fatigue conditions.

## Conclusions

This study investigated how stepwise manipulations of subjective effort (60–100%) are reflected in muscle coordination during the table tennis forehand topspin stroke. As effort increased, ball speed, ball spin, and normalized EMG amplitudes increased progressively, confirming that participants generated outputs consistent with the instructed effort levels. In contrast, the number of muscle synergies extracted by non-negative matrix factorization did not differ across effort conditions, and both global and local VAF criteria were satisfied in all cases. These findings indicate that the fundamental units of coordination were preserved across the examined effort range. Similarity analyses further demonstrated that Synergy 1 and Synergy 2 were consistently identified across all effort levels, supporting their role as basic coordination synergies underlying this skill. In contrast, Synergies 3–5 were more frequently identified at higher effort levels and were less consistently extracted under submaximal effort. These patterns were interpreted not as the formation of new coordination structures but as supplementary synergies that became more clearly distinguishable at higher effort levels. In particular, Synergy 2 contributed primarily to acceleration during the early forward-swing phase, whereas Synergy 1 was associated with deceleration and postural stabilization in the follow-through phase. Supplementary synergies exhibited phase-specific contributions, including preparatory stabilization (Synergy 4), additional acceleration before impact (Synergy 5), and stabilization around impact (Synergy 3). Taken together, the results suggest that increases in subjective effort did not reorganize the basic coordination patterns of the forehand topspin stroke. Instead, greater output was achieved through proportional scaling of activation within basic synergies, accompanied by the selective recruitment and clearer identification of supplementary synergies in specific movement phases. Thus, effort modulation functioned primarily as an output-scaling mechanism operating within a preserved coordination framework. From an applied perspective, these findings indicate that manipulating perceived effort can substantially alter performance-related outputs without changing the extracted number of coordination modules. This suggests that skilled performers are able to regulate movement intensity while maintaining stable core coordination patterns. However, because the present study did not assess training interventions or longitudinal adaptations, practical applications should be interpreted as potential implications rather than confirmed outcomes. Although the present findings were obtained from upper-limb and selected trunk muscles in skilled collegiate players, they provide a focused perspective on how subjective effort relates to muscle synergy patterns in a sport-specific striking task. In summary, subjective effort modulation in the forehand topspin stroke increased ball speed, ball spin, and muscle activation amplitude while preserving the extracted number of muscle synergies. Basic synergies remained stable across effort levels, whereas supplementary synergies became more evident at higher effort levels. These findings support the interpretation that skilled athletes increase output primarily through activation scaling and phase-specific supplementary recruitment within an otherwise stable coordination structure.

**Declaration of generative AI and AI-assisted technologies in the writing process**

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) solely to check grammar, spelling, and linguistic clarity. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication. Subsequently, the manuscript underwent professional English editing by Editage.

**Conflicts of interest**

The authors declare no conflicts of interest.

**Funding source**

This research did not receive external funding.

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