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Article

Unraveling individuality in dance through weight distribution analysis of Nihon Buyo dancers

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SUMMARY

In an age where dance has taken over social media trends, misconceptions about what it takes to become a skilled dancer may be hindering the progress of new learners. One prevalent belief is that students naturally mimic their teachers' movements, which can be measured as weight distribution, as they improve, but it is unclear whether their movements actually become more similar over time. In this study, we investigated this assumption in the context of Nihon Buyo dance by testing the hypothesis that as dancers train, they develop a distinct weight distribution profile, separate from their teacher's. By utilizing an advanced floor interface that tracks movement with high sensitivity, we monitored dancers over nine weeks of practice. Our findings revealed that learners initially exhibit a weight distribution profile distinct from their teacher's that develops to a unique, personal profile rather than to their teacher's. Our study underscores the individuality of each dancer's style and suggests that dance education should emphasize personal expression over strict imitation. It might also motivate teachers to use more adaptable teaching strategies that help students develop their unique movement patterns.

INTRODUCTION

With the rise of video-sharing platforms such as TikTok and YouTube, dancing has become a global phenomenon. It is generally assumed that as dancers improve, their movements become more closely aligned with their teacher's movements (1-2). This is evident as many dancers focus on mimicking tutorial videos, striving to replicate not only the movements but also the shifts in weight and posture of their instructors. Similarly, dance games and learning apps are designed to reward those who precisely synchronize their movements with the model dancers (3). Consequently, the dance industry operates on the belief that dancers can improve their dance by ensuring their movements converge with those of their teachers.

There is, however, an increase in support for the idea that dancers improve not just by emulating their teacher, but by adopting unique forms (2). This concept is supported by the "somatic approach" in dance pedagogy, where dancers are encouraged to realize their personal way of expressing themselves and base their movements on their internal feelings rather than external standards (2). Interestingly, despite traditional dances being highly conservative with strict rules, this dance pedagogy is particularly prevalent. In Nihon Buyo, a Japanese classical dance, for instance, dancers have a traditional master-apprentice relationship, where the learner is only exposed to their teacher's dance style (4). However, professional Nihon Buyo dancers believe that even within this teaching environment, each dancer eventually develops their unique style (5). Understanding whether dancers do develop a personal dance profile distinct from their teachers as they improve could shift the current teaching paradigms of dance and have profound implications for the dancing community.

In recent years, there has been an increasing interest in the application of digital technologies to analyze the biomechanics of dance. Studies using real-time sonification and wearable sensors have shown that dancers can receive immediate feedback on foot pressure, which helps improve learning outcomes (6). These technologies can provide a framework that can track progress and offer individualized corrections, leading to more data-informed teaching practices rather than subjective ones. Motion capture has also played a critical role in analyzing stylistic features of dance. In a previous study, systems that rely on wearable Inertial Measurement Units (IMUs) and optical tracking have been used in identifying spatial patterns, timing deviations, and dynamic changes in posture while dancing (7). Notably, some research has compared the dance techniques of students and teachers using digital video tracing tools and Dance Designer, a choreography software, to those who are not to explore how technology can be beneficial in dance instruction (8).

In the context of Nihon Buyo, a few studies have begun analyzing weight and posture through digital tools. Through motion capture, researchers have amplified differences in waist height and body openness across dance characters (9). Another study quantified bodily techniques called "Waza" through motion capture technology to understand and preserve Japanese cultural heritage (10). Together, these works demonstrate the potential of digital tools to decode traditional styles and movement in Nihon Buyo.

Despite these advances, weight distribution remains an underutilized metric in dance style and technique studies. A weight distribution profile refers to how a dancer shifts and balances their weight across the floor during movement. It is measured using pressure-sensitive technology, which captures variations in force exerted by different parts of the feet. This profile helps analyze movement patterns and track changes in technique over time. While some work has included weight analysis, it often plays a secondary role to

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more commonly studied factors like timing, posture, or spatial movement. This is mainly because it faces limitations such as hardware cost, data interpretation challenges, and limited spatial resolution in earlier floor sensor technologies (11). Recent advances in high-resolution floor sensors, however, offer the potential to overcome these challenges.

In this study, we hypothesized that, as dancers practice Nihon Buyo, they adopt a weight distribution profile distinct from their teachers. We utilized a state-of-the-art weight tracking technology, Flexel, to develop a pipeline that tracks the weight distribution profile of a Nihon Buyo dancer as they practiced (12). Our pipeline provides an accurate metric for the similarity of dance movements by evaluating the changes in load and pressure of dancers over time. We used this pipeline to test our hypothesis. By analyzing the collected data over nine weeks, we found that the learner formed their unique weight distribution profile distinct from their teacher. Our results indicate that with continued practice, Nihon Buyo dancers move beyond pure imitation and develop their distinctive movement patterns.

RESULTS

A system to quantify dancer-specific weight distribution patterns

We tested our hypothesis that Nihon Buyo adopt a weight distribution profile distinct from their teachers by developing a system to track the weight distribution and performance qualities of Nihon Buyo dancers **(Figure 1)**. We integrated Flexel boards, state-of-the-art floor interfaces, with a visual imaging system. We recorded live data simultaneously from both data sources using Unisession for Floor, an in-house developed software (12). Together, this system enabled us to quantitatively analyze the weight distribution of Nihon Buyo dancers in relation to their visual dance movements. We recorded the dances of one teacher and one Nihon Buyo learner with the Flexel and a video recorder. The teacher was recorded in one day, and the learner was recorded every week over nine weeks of practice.

Learners do not converge toward their teacher's weight distribution profile

We compared how the center of pressure of the dancers changed in the horizontal and vertical directions over time. In both the horizontal and vertical directions, the center of pressure changes of the teacher were distinct from the learner, both at the beginning of practice and after nine weeks of practice **(Figure 2)**.

Learners converge toward their own practiced weight distribution profiles

We next quantified the similarity between the weight distribution profiles of the teacher's and the learner's dance over nine weeks of practice. We utilized two metrics that are commonly used to quantify the similarity of functions: cross-correlation to account for noise and the cosine similarity for general comparisons (13). Cross-correlation assesses the time-lagged relationship between the two movement sequences, helping to identify patterns and synchronization. Cosine similarity similarly measures the alignment between two movement vectors, indicating how similar the learner's movements are to the instructor's. In both cases, a value of one represents perfect similarity, while values closer to zero suggest less similarity. When the learner's weight distribution profiles were compared to the teacher's, the learner's weight distribution profiles did not show signs of becoming similar to the teacher's **(Figures 3A and B)**. A notable difference in movement patterns can be seen in the graphs identifying the cosine similarity, where there is a notable decline, especially when comparing the learners' week 2 and week 9. In contrast to the previous results, the similarity between the learner's dance and the learner's dance after nine weeks of practice showed a converging pattern wherein as the learner accumulated more time learning the dance, their weight distribution profile became more similar to the learner's dance after nine weeks of practice **(Figures 3C and D)**. This was the case for both metrics.

We validated our findings by comparing the learner's dance at each time point to week one. In concordance with our previous results, we found that in both the horizontal and

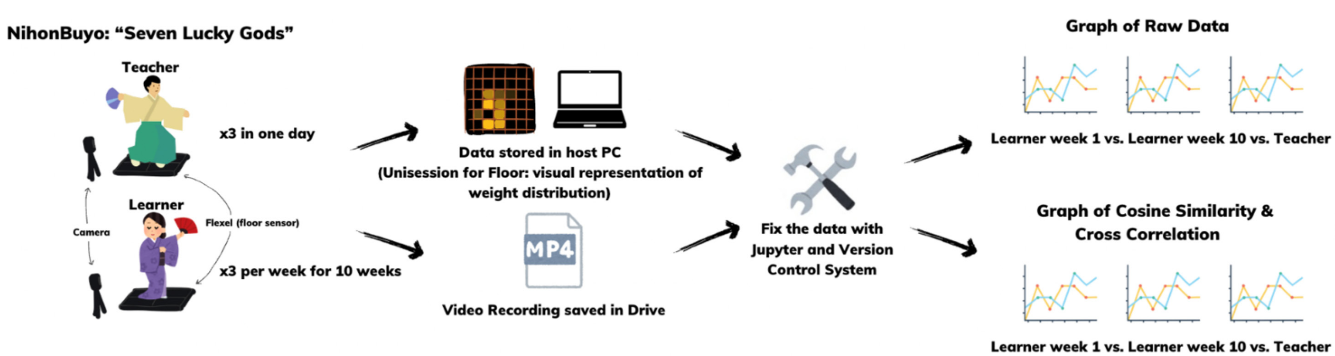

Figure 1: Summary of research pipeline. Schematic of process for collecting, processing, and analyzing weight distributions of Nihon Buyo dances by the learner and the teacher. The learner practiced the Nihon Buyo piece "Seven Lucky Gods" three times per week for nine weeks, while the teacher performed the same piece three times on a single day. Both participants danced on the Flexel floor sensor, which captured detailed weight distribution data (12). Simultaneously, a camera recorded each session for reference. Sensor data were stored on a host PC using Unisession for Floor, enabling visual representation of foot pressure and weight distribution. The video recordings were saved to a shared drive. Data were then cleaned and processed using Jupyter and a Video Studio Code. Analysis included visualizing raw weight distribution data and computing cosine similarity and cross-correlation between the learner and teacher across time points (e.g., learner week 1 vs. week 9 vs. teacher).

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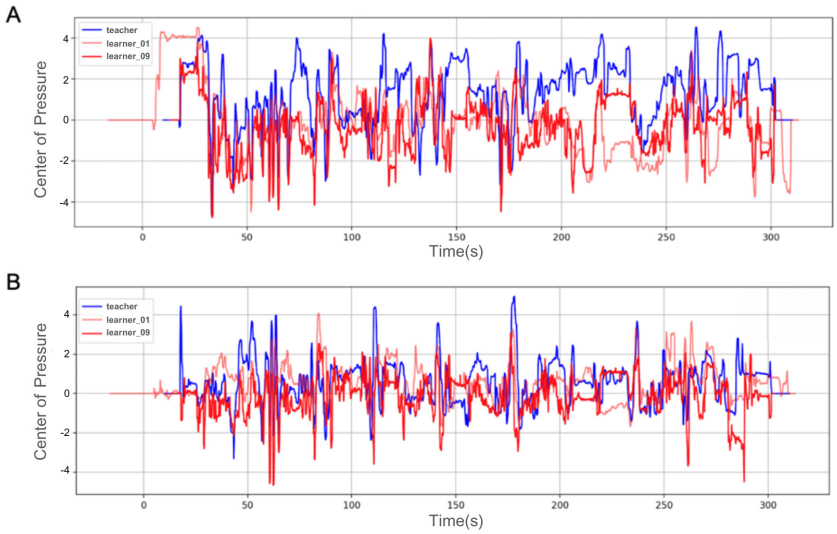

Figure 2: Comparison of changes in the center of pressure over. Displacement of the center of pressure on the **A)** horizonal and **B)** vertical directions of the floor sensor for the teacher and learner. Lines are colored by the dancer: teacher (blue), learner after one week of practice (light red), and learner after nine weeks of practice (red).

vertical directions, from week 1 to week 8, the dancer's similarity with the teacher did not significantly increase **(Figures 4A and B)**. In contrast, the similarity with learner's dance after 9 weeks significantly increased from week 1 to week 8 (for horizontal, p = 0.002 and for vertical, p=0.004), highlighting the robustness of our findings **(Figures 4C and D)**.

To quantitatively test our hypothesis further, we focused on comparing the weight distributions of specific dance movements **(Figure 5)**. We repeated the previous analysis, evaluating the cross-correlation and cosine similarity of the dancers for sections of the dance where the dancers performed specific Nihon Buyo movements: hopping on one foot, preparing the bow, hitting the drums, and standing up and rotating on one foot **(Figure 5A–H)**. In each of these dance movements, the learner's weight distribution profile did not become more similar to the teacher's as they practiced. A noticeable drop in movement similarity was observed in week 3 **(Figure 5B)**. In contrast, the similarity between the learner's dance in week one and week nine showed a converging pattern, corroborating our previous findings.

DISCUSSION

We tested our hypothesis that as Nihon Buyo dancers practice, they adopt a weight distribution profile distinct from their teachers by utilizing a sensitive weight device called Flexel. By calculating the cross-correlation, which measures the temporal alignment between two signals, and cosine similarity, which assesses the directional similarity between two multidimensional vectors, we accurately identified the differences between the teacher's weight distribution profile and the learner's weight distribution profile: with an increase in time, the learner developed their weight distribution profile distinct to their teacher, which was demonstrated by the increase in both the cross-correlation and cosine similarity between the learner and the learner's weight distribution profile after nine weeks of practice. To our knowledge, our study is the first to utilize a floor tracking device to track and analyze the weight distribution of traditional Nihon Buyo dance.

In our study, we observed that the center of pressure shifts for the teacher differed from those of the learner in both the horizontal and vertical directions, both at the start of practice and after nine weeks of practice **(Figure 2A and 2B)**. This indicated that the learner, even after practice, had a distinct weight distribution profile from their teachers. We also found a clear difference in movement patterns, as illustrated by the cosine similarity graphs, which show a marked decline, particularly when comparing the learner's results from week 2 to week 9. This indicated that the learner was not adopting a similar weight distribution profile to the teacher as they practiced, for both metrics in both the horizontal and vertical directions **(Figures 3A and B)**. Additionally, we observed a noticeable drop in movement similarity in week three **(Figure 5B)**. While the cause was not explicitly documented, this deviation may be due to external factors such as fatigue, temporary difficulty with specific movements, or attentional distractions during that session. Together, these findings indicate that as Nihon Buyo dancers practice a fixed routine, they develop a weight distribution profile distinct from their teachers, supporting our hypothesis that dancers adopt personal weight distribution profiles for different dance movements.

There are several limitations in our study. First, data was only gathered from one teacher and one learner that have worked together for a long time. This, therefore, fails to represent the different types of teacher-student dynamics that may exist. Second, we focused only on Japanese traditional dances. Since we chose a very specific dance style, the results may not represent other traditional dances, or even dance in general. Third, the learner only learned the choreography of the dance in person for the first week, and in the following weeks, the learner used a device with the teacher's recording. This could have affected how the learner interpreted the dance since learning from a recording is different from directly learning from the teacher. Fourth, this study does not account for innate biomechanical traits, such as muscle imbalances or skeletal alignment, as well as height and weight differences, which could inherently influence weight distribution profiles (14). Lastly, we used floor sensors to track weight distribution profiles and assumed that these measurements would

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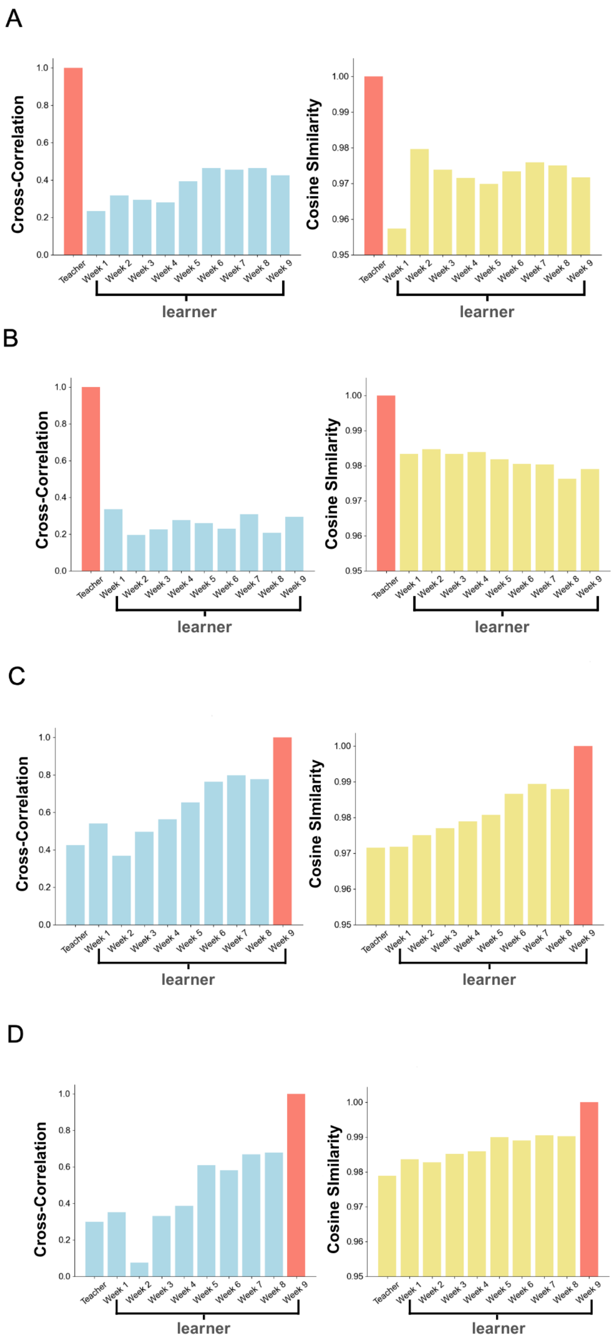

Figure 3: Quantitative comparison of the center of pressure changes of the learner and the teacher. Cross-correlation and cosine-similarity between the center of pressure changes during the whole dance in the **A)** horizontal and **B)** vertical directions between the learner (over nine weeks of practice), and the teacher. The center of pressure changes of the learner were recorded every week over nine weeks. Cross-correlation and cosine-similarity between the center of pressure changes during the whole dance in the **C)** horizontal and **D)** vertical directions between the teacher and the learner over nine weeks of practice and the learner after 9 weeks of practice. The red colored bar indicates the reference for all graphs.

represent the overall weight distribution of the dancers. There could be other factors, such as the movement of the hand choreography, posture, and upper body movements, that play a role in shaping the weight distribution profile of dancers that cannot be measured by our floor sensor.

To improve our study, future works should incorporate a larger sample of teachers and learners to account for the broader range of different teacher-to-student dynamics, as well as include other motion-tracking devices to have a more comprehensive understanding of how specific movements can affect the overall weight distribution profile (15). Moreover, future studies should systematically investigate factors such as prior dance experience, physiological differences, and motor learning styles to better understand the emergence of individual weight distribution patterns within structured practices like Nihon Buyo. Beyond these, we suggest developing structured observation protocols to systematically record contextual factors such as fatigue, emotional state, or instructional changes that may influence learner performance.

Our study, which mainly focuses on traditional dance, has the potential to contribute to the broader world of dance education. While traditional dances typically emphasize adherence to the strict forms and techniques that already exist in that culture, our findings show that even with practices that are highly structured, the learner will eventually develop their own dance style and weight distribution. For educators in traditional forms such as Nihon Buyo, this highlights the value of incorporating motion-sensing technologies to better understand each learner's unique movement tendencies. Rather than enforcing a singular "ideal" form, instructors can support personalized instruction, offering corrections or adjustments that respect the dancer's natural style while guiding them toward greater technical precision. This approach demonstrates how technology can refine traditional pedagogy and contribute to the sustainable transmission of culturally significant practices. By focusing on a traditional form of dance, our study provides new insight into the knowledge of dance pedagogy, particularly highlighting the uniqueness of each dancing style for each individual.

MATERIALS AND METHODS

Student and teacher demographics

The learner was a 15–25-year-old female who began practicing Nihon Buyo in 1st grade under the teacher. She performs twice every year and used to perform at nursery homes. The teacher is a 40–50-year-old, and has performed internationally. The teacher also has extensive training in the art of Nihon Buyo and has graduated from the Tokyo University of the Arts in traditional Japanese music.

Procedure

To ensure that the learner executed each movement correctly, all sessions were video recorded. The instructor regularly reviewed the footage and conducted periodic check-ins during practice to confirm accurate performance and provide immediate feedback or corrections as needed. This allowed us to verify that the learner's movements aligned with the traditional Nihon Buyo technique.

Measuring weight pressure distribution

The weight pressure distribution of dancers was measured by Flexel, a modular floor interface. Flexel can sample

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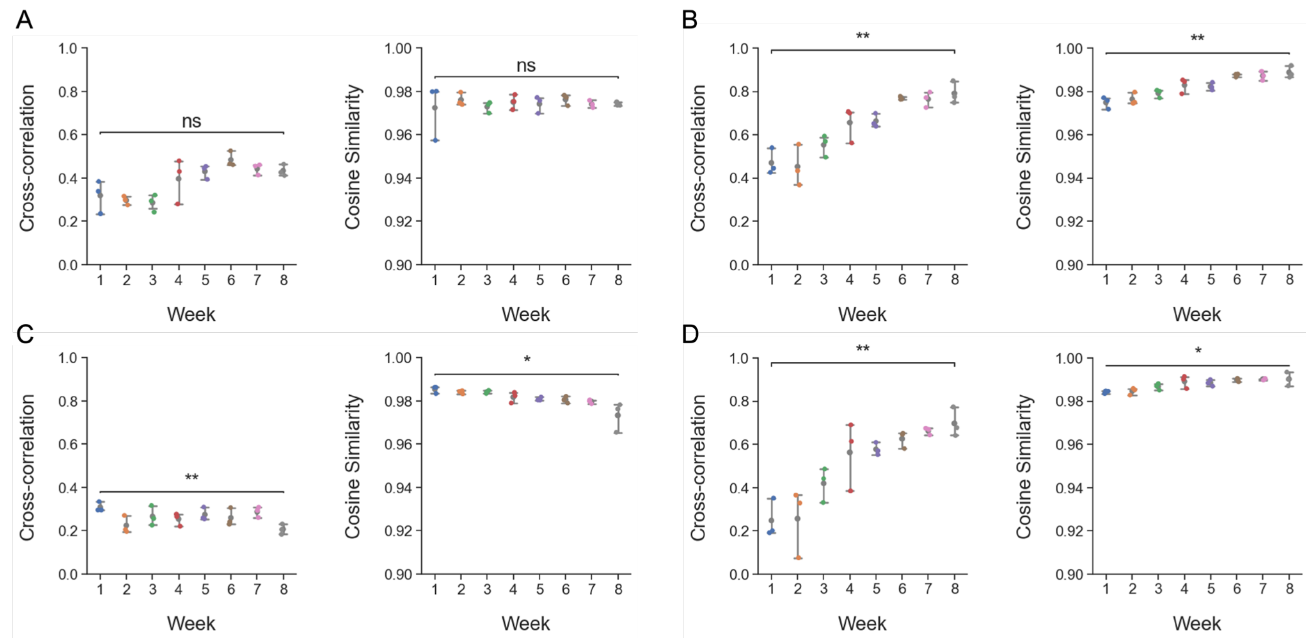

Figure 4: Center of pressure similarity between learner and teacher across repeated trials. Cross-correlation and cosine similarity between the learner's center of pressure changes in the **A)** horizontal and **B)** vertical directions, comparing the learner's performance across eight weeks to the teacher. Each point within a week represents one of three repeated trials. Cross-correlation and cosine similarity between the learner's center of pressure changes in the **C)** horizontal and **D)** vertical directions, comparing the learner's performance across eight weeks to the expert learner (week nine). Each point within a week represents one of three repeated trials. Asterisks indicate statistical significance based on repeated trial comparisons within each week: *$p < 0.05$, **$p < 0.01$, and ns denotes nonsignificant differences ($p > 0.05$). Statistical testing by independent t-tests, comparing weeks 1 and 8, with 95% confidence intervals calculated by bootstrapping.

the pressure distribution at 80Hz, and in every square meter of floorboard, there are 144 load cells installed (12). We used four of these floorboards to capture the weight pressure distributions of the dancers, creating an area of length and width of two square meters each to dance on.

Collecting dance data

To create the teacher's dance data, we recorded a professional dancer performing a dance of their choice ("Seven Lucky Gods"). We then asked the learner to learn the same dance over nine weeks. The learner had access to a recording of the teacher's dance during this timeframe. Each session lasted approximately three to five minutes, during which the learner performed a full run of the dance three consecutive times every week. All recordings were conducted under researcher supervision to ensure the dancer remained within the floorboard area and followed consistent procedures. The weight distribution data were captured in real time and stored via the connected host PC, while simultaneous video recordings were saved to a shared drive.

Preprocessing the data

We processed the data using Jupyter Notebook (v7.2.1). We first determined the x and y center of mass of the dancer by finding the average of the x-axis and y-axis and locating a point with those x and y values recorded on the floorboards **(Equations 1 and 2)**. These equations calculate the center of pressure (COP) in both the x and y directions. The COP represents the average location of all forces acting on the surface, essentially indicating where the body's weight is concentrated. In the equations, x_i and y_i are the positions where force is applied, while F_i represents the amount of force at each point. The total force, F_{total}, is the sum of all these individual forces. By taking the weighted average of these positions, the COP helps analyze balance and weight distribution, which is crucial in studying movement control. In the figures, the CoP sensor data is represented in pixel units of floor sensor. To convert the pixel values into centimeters, they should be multiplied by 8.3, as there are six sensor units per 50 cm (50/6 = 8.3).

$$x_{COP} = \frac{\sum_1^n (x_i \cdot F_i)}{F_{total}} \qquad \text{(Equation 1)}$$

$$y_{COP} = \frac{\sum_1^n (y_i \cdot F_i)}{F_{total}} \qquad \text{(Equation 2)}$$

We reduced noise by removing any outlier data points: we removed any datapoint where the center of mass differed from the previous frame by over eight centimeters in either the horizontal or vertical direction. Finally, for comparison of data, we adjusted the start time of the data to match one another based on when the dance started in the video.

Data analysis

All of the data was stored in the host computer. Afterward, the data was analyzed through Jupyter Notebook and Visual Studio Code (v1.86). The analysis focused on comparing weight distribution patterns between the professional and intermediate dancers to assess stability and performance quality. For targeted comparison, we examined weight distributions during specific motions: 'Hopping on One Foot' (74–88 seconds), 'Preparing the Bow' (89–94 seconds), and 'Hitting

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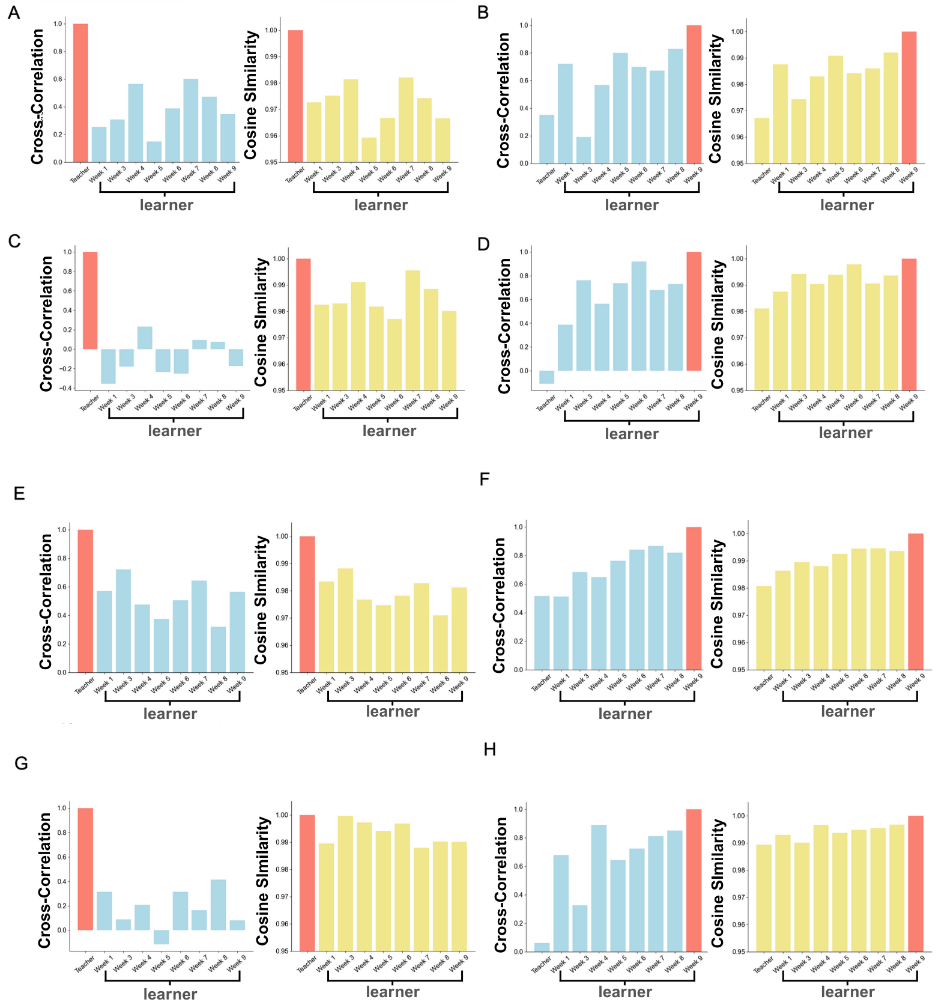

Figure 5: Quantitative comparison the center of pressure changes for specific dance movements. Cross-correlation (blue) and cosine-similarity (yellow) between the center of pressure changes during specific dance movements in the horizontal direction. **A–B)** “Hopping on One Foot” (74–88 seconds) with the reference set to **A)** the teacher and **B)** the learner at week 9. **C–D)** “Preparing the Bow” (89–94 seconds) with the reference set to **C)** the teacher and **D)** the learner at week 9. **E–F)** “Hitting the Drums” (134–144 seconds) with the reference set to **E)** the teacher and **F)** the learner at week 9. **G–H)** “Hitting the Drums” (146–156 seconds) with the reference set to **G)** the teacher and **H)** the learner at week 9. The red bar indicates the reference for all graphs.

the Drums’ (134–144 seconds and 146–156 seconds into the dance).

To compare the data of weeks one to nine of the learner, and the teacher, the cross-correlation **(Equation 3)** - measurement of how well two independent signals resemble each other, and the cosine similarity **(Equation 4)** - a measurement of the similarity between two vectors of an inner product space, were used as defined below.

$$r_{xy}(l) = \sum_{n=-\infty}^{+\infty} x(n)y(n-1) \quad \text{(Equation 3)}$$

$$similarity(A,B) = \cos(\theta) = \frac{A \cdot B}{|A|\,|B|} = \frac{\sum_{t=1}^{n} A_t B_t}{\sqrt{\sum_{t=1}^{n} A_t^2}\sqrt{\sum_{t=1}^{n} B_t^2}} \quad \text{(Equation 4)}$$

Specifically, **Equation 3** represents cross-correlation, which measures how two movement signals change in relation to each other over time. The function sums the product of one movement signal *x(n)* and a time-shifted version of another signal *y(n−1)*. By adjusting the shift *l*, we can determine whether one movement follows another with a delay. This helps identify timing relationships between the dancer and the teacher, such as whether the student consistently lags or moves in sync. **Equation 4** measures the similarity between two movement patterns using the cosine similarity formula. It compares two sets of movement data, represented as vectors A and B. The numerator $\sum A_i B_i$ calculates how much the two movements overlap, while the denominator normalizes the values to ensure the similarity score stays between 0 and 1. A score closer to 1 means the two movements are highly similar, while a score near 0 suggests little to no similarity.

Statistical analysis

Statistical analysis was performed using independent t-tests to compare group means. For each comparison, 95% confidence intervals were calculated using a bootstrapping approach with Seaborn in Python.

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