Kinematics of Bowing the Re-Strung Violin

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ABSTRACT

KINEMATICS OF BOWING THE RE-STRUNG VIOLIN

Sarah Hayden, B.S.
Marquette University, 2024

Building upon existing research in motor learning and sensorimotor control, this thesis explores how the performance of a real-world task (playing a simple musical piece on the violin) is impacted by the spatial re-arrangement of the violin’s strings, and how performance recovers with practice (relearning). I recorded audio performances and bow kinematics as violinists with a wide range of prior skills played a familiar 2-octave G-Major arpeggio 50 times. Some subjects played all 50 arpeggios on a violin with the standard string arrangement (the control violin). Another set of subjects played the middle 30 arpeggios with a “similar” violin with an inverted string arrangement, preserving the typical nearest-neighbor relations among the strings. A third set of subjects played the middle 30 arpeggios with a “dissimilar” violin having a shuffled string arrangement that destroyed the typical nearest-neighbor relations. Results showed a transient effect on audio performance from the string re-ordering; this effect decreased across the 30 test trials consistent with re-learning. Contrary to expectations established in a related lab-based study, subjects relearned faster with the less similar violin (shuffled) compared to the more similar violin (inverted); additionally, there were after-effects on performance when subjects returned to the normal violin, but only after playing the inverted violin. By contrast, bow kinematics showed sustained disruption during the 30 test arpeggios. I observed no after-effects of exposure to either test violin on bow kinematics when subjects were again given the normal control violin. Whereas previous studies have reported facilitative effects of geometric similarity on motor learning, this investigation found the opposite effect: violin performance was disrupted more when playing the “similar” inverted violin than the “dissimilar” shuffled violin. This performance effect was not impacted by prior skill level even though some aspects of bow kinematics did vary with prior skill. Overall, this thesis contributes to the growing body of knowledge in motor learning and sensorimotor control, offering valuable insights into the factors influencing motor relearning in complex tasks like violin performance.
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CHAPTER I

I. RATIONALE & SPECIFIC AIMS

Motor re-learning is a process by which the nervous system generates new patterns of movement coordination in response to new behavioral needs and environmental conditions. Motor re-learning involves restructuring existing coordination patterns to adapt to new situations, particularly when previous solutions are no longer viable. Motor re-learning is crucial for successful action performance despite growth, development, and recovery from injuries. Understanding how experience with a task influences individuals' adjustment of coordination in response to environmental changes poses significant questions: Is it easier to learn a task similar to what you have already learned, or does prior experience interfere with learning? In my study, I address these challenges by performing human subject experiments in a real-world performance setting while employing rigorous techniques including a valid control group. My study aims to investigate how people reorganize patterns of coordination when learning tasks with different levels of similarity to a previously acquired skill, and how prior experience/skill level impacts the reorganization of coordination patterns. The task in this study is the playing of a simple arpeggio on the violin. Understanding the process of motor re-learning is crucial for advancing knowledge of sensorimotor control.

Previous studies of motor relearning have approached this problem through experiments in the research lab. This is because studies in real-world settings face challenges in establishing precise experimental controls. As a result, lab experiments often involve artificial scenarios that may not accurately mimic real-life situations. Although some previous studies in laboratory settings have focused on how physical
alterations to the violin affect sensorimotor control in skilled performers (Morreale et al. 2018), I propose a novel approach that extends beyond mere physical modifications. Building upon existing research, which has predominantly examined simplified tasks and controlled conditions, my study seeks to explore the reorganization of coordination patterns in violinists within the context of real-world performance scenarios. By integrating insights from both laboratory experiments and studies involving altered instruments, I aim to overcome these challenges to enhance our understanding of how prior motor skills influence adaptation to new tasks, particularly in violin playing. My specific aims are:

- To investigate how violinists reorganize coordination patterns influencing bow motion when faced with changes in their instrument's string configuration, and
- To determine how the violinists' current skill level influences this adaptation process.

In partnership with the Music Institute of Chicago's Summer Suzuki Institute, I used precision motion tracking technology to collect violin and bow motion data from approximately 100 violinists performing 50 repetitions of a simple, well-known piece of music - a two-octave G-Major arpeggio played in first position. Violinists were divided into three groups: one only played a standard (control) violin whereas the other two played some repetitions with one of two possible alternate violins, which differed from the control violin in ways that either did or did not preserve a sense of similarity with the control violin. I then analyzed the resulting data to evaluate the impact of similarity on
how violinists re-organized their bow motions and the extent to which current skill level impacts this re-organization. This investigation will provide valuable insights into the mechanisms underlying sensorimotor adaptation in violin performance.

This chapter sets the stage for what follows. The next chapter will review existing research, including studies on how violinists move while playing their instrument. I will also discuss how patterns of coordination change when the violin setup changes (i.e., via motor re-learning). Afterward, I will explain the methods I used in my study, share my findings, and discuss what they mean for an understanding of the kinematics of bowing the violin. Finally, I will look at where future research could go and how this work might be applied practically.
II. BACKGROUND

A. Introduction

To interact successfully with the world, a person must successfully learn how objects respond to their actions through a process known as sensorimotor learning. Through sensorimotor learning, a person can come to recognize causal patterns in the actions and reactions inherent to the cycles of perception-action-cognition that define how they engage with the world. Over time, a person can refine their actions to achieve desired reactions from objects in the environment through a process of skill learning. Because the world is unpredictable and objects can sometimes change without awareness, a person sometimes must adapt or otherwise re-learn the action/reaction patterns that define skilled behavior. The question of how people relearn patterns of behavior in response to changing environmental conditions has been studied for many decades, usually using very simple tasks performed within the highly controlled conditions of the research laboratory (Kelleher et al., 2013). This chapter aims to examine the extent to which the relearning of skilled performance has been studied within the context of one of the most challenging real-world tasks: playing the violin.
B. Kinematics of Bowing the Violin

Three-dimensional (3D) motion capture techniques are typically used to record and analyze the biomechanics of bowing the violin. 3D motion capture approaches include the use of photography, video analyses, optical markers, and more. These tools allow for spatial analysis of movement as well as 3D reconstruction of movement using a 2D video projection (Cohen, 2017).

Schoonderwalt et al., (2009) described procedures to quantify the kinematics of violin bowing. Figure 1 (top) depicts two reference frames: one fixed to the bow \{\hat{x}_B, \hat{y}_B, \hat{z}_B,\} with the -\hat{x}_B axis directed along the long axis of the bow, and a second fixed to the violin \{\hat{x}_V, \hat{y}_V, \hat{z}_V,\} with the \hat{y}_V axis directed along the strings toward the scroll. Using these reference frames, it is possible to compute the three angles commonly used to describe bow kinematics: skew, inclination (or attack), and tilt.

The skew angle (skewness) describes the deviation of the bowing direction from perpendicularity to the string in the plane of the violin (Equation 1; Schoonderwalt et al. 2009).

\[ \varphi = \frac{\pi}{2} - arccos(\hat{y}_V \cdot \hat{x}_B) \] (1)
By convention, the skew angle is considered positive when the frog (the part of the bow that the hand holds) is pointed away from the player's body.

The inclination angle is typically associated with playing different strings (Equation 2; Schoonderwalt et al. 2009):

\[
\theta = \arccos(\hat{z}_V \cdot \hat{x}_B) - \frac{\pi}{2}
\]  

(2)

By convention, the inclination angle is considered positive when this angle moves from lower to higher-pitched strings.

The tilt angle is computed as the angle between a plane parallel to the length of the axis of the bow ($\vec{x}_B$) and the string ($\vec{y}_V$), and a line with the direction of ($\vec{y}_B$) (Equation 3; Schoonderwalt et al. 2009).

\[
\psi = \arccos\left(\frac{\vec{x}_B \times \vec{y}_V}{|\vec{x}_B \times \vec{y}_V|}\right) - \frac{\pi}{2}
\]  

(3)

By convention, positive tilt is defined as the stick leaning toward the fingerboard (rather than the bridge) and is zero when the hair is flat on the string.

To collect the data described in this thesis, I used an Optotrak 3020 motion capture system with active infrared (IRED) markers rigidly fixed (hot glued) to the violin and bow as described in Figure 2. I collected real-time bow and violin motion data at 100 frames per second. For each "frame" of data, I use the approach described by Schoonderwalt and colleagues (2009) to quantify the kinematics of bowing. As I will...
describe in the following chapters, I focus my analyses predominantly on the skew and inclination angles because estimates of tilt angle are unreliable without significant alterations to the configuration of the bow, as was done in Schooderwalt's study.
C. Sources of Kinematic Variability in the Measurements of Bow Kinematics

In 1998, Turner-Stokes and colleagues analyzed-musicians playing a variety of stringed instruments (violin, viola, or cello) under several test-retest conditions to characterize sources-of variability in the motion capture and kinematic analysis of arm movements while bowing (Turner-Stokes, 1998). Data capture was performed with a 3-camera setup with retroreflective markers enabling full 3-D motion capture and estimation of the players’ shoulder, elbow, and wrist motions. During motion capture, subjects were to perform 12 cycles of slow legato bowing across all four open strings, with 4 beats per bow per string at 100 beats per minute. Test-retest consistency of the data collection protocol was assessed in 3 subjects (two violinists and one cellist) across 4 testing sessions. The system was calibrated prior to data collection Session 1, where the subjects sat in a chair and played their instrument. The data collection volume was recalibrated and the subject repositioned within it prior to Session 2. The subject's markers were removed and replaced between Session 2 and Session 3. Finally, the whole data collection system was dismantled and reassembled between Session 3 and Session 4, which occurred on different dates.

The motion capture approach described by Turner-Stokes and colleagues performed well under all three test-retest conditions. Between Sessions 1 and 2 where the data collection volume was recalibrated and the participants re-positioned within that volume, test-retest differences as a percentage of the mean angle for the angular range of motion at the shoulder, elbow, and wrist were 8.3%, 3.8%, and 5.8%, respectively. Between Sessions 2 and 3 where the retroreflective markers were removed from the subject and then replaced, test-retest differences for the angular range of motion at the
shoulder, elbow, and wrist were 6.5%, 4.2%, and 9.3%. Between Sessions 3 and 4 with the subject returning at a second date after the entire system had been dismantled and then reassembled, the authors observed a 9.7%, 4.0%, and 6.7% difference in the mean angle at the shoulder, elbow, and wrist joints. Based on these results, the authors concluded that motion capture during the bowing of stringed instruments yields reproducible results regardless of instrument (Turner-Stokes, 1998).
D. Skill Acquisition and the Organization & Reorganization of Coordination Patterns

When a performer practices the violin for a long period of time, they will reach a point where the sensorimotor mechanisms can predict changes in the state of the instrument, the body, and aspects of group performance such that they can respond with motor commands that not only reflect great precision of control but also great flexibility and ability to adapt to ever-changing demands of group performance.

This flexibility has been studied experimentally by Morreale and colleagues, who examined how physically altering the violin might affect sensorimotor control of a well-learned task (Morreale et al. 2018). The study subjects included seven professional violinists. They were given pieces of sheet music to sight-read as well as repertoire pieces to perform. These musical pieces were to be played on four different violins: the performer’s personal violin, a cheap violin, a quarter-sized child’s violin, and a violin altered such that the conventional string arrangement on the violin was reversed (i.e., inverted). The cheap violin was unaltered in comparison to the subject’s personal violin, but it was chosen to test the subject’s sensitivity to their personal violin. The smaller violin was chosen to determine the subject’s sensitivity to violin technique in comparison to the scaling difference. The reverse-stringed (inverted) violin was chosen to test how altering the geometric arrangement of the strings would impact performance. Markers were attached to the violin and subject so that the motion capture system would track and record the bow-instrument interaction. Each performance also was videotaped, and audio was recorded.
The violinists' performances were assessed using quantitative measures of the pitch (intonation) and duration of notes played, as well as kinematic measures of bowing gestures and errors. This study had multiple results of interest. Overall, the subjects were less precise (more variable) in their intonation with the smaller and inverted violins predominantly at the beginning of played notes, although pitch accuracy improved throughout the duration and at the end of the played notes in these violins. The authors inferred from these findings that the feedforward plans for movement (which the authors call "sensorimotor predictions") are not sufficiently malleable to compensate for differences in scale and string orientation before auditory feedback arrives.

The violinists struggled to play a well-known repertoire piece (a Bach Courante) without slowing down or halting when playing the violin with altered string ordering - but not any of the other violins. All performers on the inverted violin produced halting performances and a significant number of bowing errors. From these results, the authors conclude: "The results support my hypothesis that axis-inversion requires performers to use conscious attention rather than established internal models to perform a piece thus resulting in a non-fluent performance."

Finally, the authors analyzed videos of performances and identified 4 types of bowing errors: wrong string errors (WS), double stop errors (DS), open string errors (OS), and wrong finger errors (WF). Bowing errors were frequent on the inverted violin but were rarely observed with the other violins. Across the cohort of 7 participants, WS errors were the most frequent errors when playing the inverted violin, occurring approximately 1.6 times more frequently than DS errors, 6.8 times more frequently than WF errors, and 11.7 times more frequently than OS errors. This suggests a significantly
higher likelihood of WS errors compared to OS and WF errors. The most common type of WS error was to swap the D and A strings, matching how the musical passage would be played if the violin were strung normally. From these results, the authors conclude that performances demonstrated "continued coordination between the left and right hand even as the action is inappropriate for the layout of the instrument."

Limitations of the study by Morreale and colleagues arise from the fact they only studied performances from a small number of professional violinists (Morreale et al. 2018). The experiments I describe and analyze build on this prior work by examining how violinists with a wide range of prior experience play a well-known musical piece on conventional and re-strung violins.
E. Variations in Bow Kinematics as a Function of Violinist Skill Level

In 2009, Konczak and colleagues studied how skill level affects bowing movements while playing the violin (Konczak et al., 2009). The authors tracked arm motion using a multi-camera motion tracking system and spherical reflective markers placed on the participant’s bowing arm. To detect displacements of the bow and violin during play, they applied light-reflecting tape to the tip and frog of the bow and to the chinrest and scroll of the violin. The subjects included four adults and 10 children, all of whom were trained through the Suzuki violin program. The Suzuki program has a pedagogical approach that includes instructing a predefined canon of musical pieces in a specific order (Konczak et al, 2009). All students start their study of the violin by

Figure 3: Left: Bow/violin skew angles as a function of time during the performance of “Twinkle, Twinkle, Little Star.” for four participants. Right: Histograms of bow/violin skew angles during performance for those participants. Figure reprinted from Konczak et al. (2009) with permission.
learning to play “Twinkle, Twinkle, Little Star.” Konczak and colleagues chose "Twinkle" as the musical piece for subjects to play because all of them had achieved mastery of this piece by the time of the study. All participants played their own violins and bows in the traditional standing performance stance. Data analysis during performance focused primarily on bow skew angles and on shoulder and elbow angles.

Figure 3 (left) presents bow skew angle measurements as a function of time during the performance of the required piece of music for four individuals: an adult expert (top), a child advanced player, an adult novice player, and a child novice player. Figure 3 (right) shows histograms derived from the corresponding panels on the left. These individual-subject data suggest that skew angle variance decreases as skill level increases in both children and adults. This was indeed the case; across the cohort of participants, skew angle variance decreased significantly as a semi-log function of estimated hours practiced (Figure 4).

Biomechanical analysis of data from markers fixed to the arm shows quantitatively that shoulder and elbow joint angle variations during bowing decrease as a function of skill level (Figure 5). As described in the paper, the dashed line in each panel
indicates the approximate slope of the angle-angle data. A steeper slope indicates the coupling rate between shoulder and elbow motion whereas a slope of 45° implies that elbow and shoulder angle changed at the same rate; a flatter slope indicates that changes in shoulder motion are smaller than in elbow motion. In this figure, the slope between shoulder and elbow motion was steepest in the beginner when compared with the advanced and expert players, which means that the shoulder and elbow moved together. When the authors analyzed shoulder and elbow angle motions across the whole cohort of participants, they found that the reduction in bowing-angle variability was strongly associated with a reduction of shoulder-angle range of motion (ROM) and shoulder-angle variability. The authors conclude therefore that learning to play the violin is not associated with a release of degrees of freedom, but rather by an experience-dependent suppression of sagittal shoulder motion (Konczak et al, 2009). It is not yet known the extent to which motor re-learning as described by Morreale and colleagues (2018) is facilitated or interfered with by skill-dependent constraints on movement kinematics as exemplified in Figures 4 and 5.

Figure 5: Plots of shoulder angle vs. elbow angle during the performance of "Twinkle" for three participants revealing patterns of inter-joint coordination. Figure reprinted from Konczak et al. (2009) with permission.
Ranganathan and colleagues investigated how prior learning influences subsequent motor skill acquisition, a critical endeavor for unraveling the mechanisms governing skill transfer and interference (Ranganathan et al. 2014). In their study, participants engaged in learning to manipulate a computer cursor via a data glove, practicing a preliminary task unique to each group alongside a shared criterion task. The mapping of finger motions to cursor positions in the preliminary task delineated task spaces with or without shared dimensions compared to the criterion task. Participants executed finger motions to navigate a virtual point between targets displayed on a computer screen using the data glove, while signals from 19 bend sensors on their fingers were recorded at a sampling rate of 60 samples per second.

Performance metrics encompassing movement time, endpoint error, path length, exploration index, planarity of hand postures, and null space dispersion were meticulously gauged. Through rigorous statistical analyses, performance metrics were juxtaposed across groups and practice blocks in both the preliminary and criterion tasks. Remarkably, participants demonstrated enhanced performance in the criterion task when the preliminary task shared task space dimensions with it, exemplifying facilitative effects. Conversely, protracted interference manifested when the preliminary task lacked shared task dimensions, yielding suboptimal task solutions. Furthermore, the extent of interference and transfer effects between tasks was influenced by null space exploration and dispersion, illuminating the intricate interplay between task space dimensionality and motor learning outcomes.
As discussed in Ranganathan’s “Organizing and Reorganizing Coordination Patterns,” the concept of learning how new coordination patterns are organized and reorganized given a specific task, playing the violin in this case, is of high interest to the sensorimotor control research field. Understanding the relationship between geometric similarity and string ordering on the violin will provide valuable insights into how musicians adapt their motor coordination to the constraints of a new task. For instance, when the strings of the violin are reversed, the geometric similarity between the control violin and the inverted violin is preserved, maintaining nearest-neighbor relationships. However, shuffling the string order disrupts these relationships, resulting in a string ordering less akin to the control violin's arrangement than the inverted violin's. My research will showcase the intricate interplay between geometric similarity and motor coordination in musical performance. The possibility of facilitation and interference will be examined both when subjects are first introduced to their test violin, as well as near the end of the test block where potential prolonged effects could be seen.
Learning to play a piece of music requires learning the movement patterns necessary to play a given sequence of notes in a prescribed manner. When learning and relearning these coordination patterns, it is typical to search for sequences. Sequence learning is fundamental to human performance (Clegg, 1998). To examine the value of sequential learning, Nissen and Bullemer performed a study highlighting the significant difference in reaction times between sequential and random stimuli. Their motivation was to assess whether patients with amnesia could acquire new associations despite memory impairments. Participants, including individuals with Korsakoff’s syndrome and healthy controls, completed a keyboard button-pressing sequence learning task involving repeated and random sequences of stimuli presented on a computer. There were four locations where the stimulus (an asterisk) could appear on the computer screen, corresponding to keys topped in white felt on the keyboard. In the sequence group, the asterisk appeared in a specific sequence: D-B-C-A-C-B-D-C-B-A. As seen in Figure 6, the decrease in reaction time from the beginning to the end of the trial for the random group was 32 milliseconds, whereas the sequence group reaction time decreased by 164 milliseconds.

Reaction times and accuracy rates were recorded for each trial block, and subjective reports regarding awareness of the repeating sequence were collected. The data
were analyzed using a three-way analysis of variance (ANOVA) with factors including group (Korsakoff vs. control), condition (repeating vs. random), and block (four blocks of trials). Additionally, patterns of chunking in response latencies were examined by computing the median reaction time to each element in the sequence across blocks and conducting further statistical analyses to identify significant effects. The findings revealed that patients with Korsakoff's syndrome demonstrated learning of the sequence task despite their lack of awareness of the repeating pattern. Their performance improved over blocks of trials, similar to healthy controls. These results challenge the view that amnesia involves a selective deficit in storing attended information and suggest that attention plays a crucial role in learning.

Furthermore, the study's results have implications for learning in other domains, such as music. Sequences are prevalent in musical pieces, particularly in violin playing, where embedded sequences are present, especially in arpeggio scales. The study suggests that performers can develop automatic sensorimotor responses to these sequences, raising questions about how quickly they can relearn the sequences if the violin is altered.
H. Knowledge Gap Assessed by My Study

The impact of similarity on re-learning in the context of a real-world task has not been extensively explored in previous studies. Specifically, while prior research has investigated how physical alterations to the violin affect sensorimotor control and adaptation, there is a lack of understanding regarding how variations in task similarity influence re-learning processes in authentic performance settings. This gap in the literature highlights the need for further investigation into the role of task similarity in motor adaptation and skill re-acquisition, particularly in complex tasks such as violin playing.

While Nissen’s study concluded a decrease in reaction times with a repeated sequence, it did not evaluate how skill acquisition is characterized by sequence learning. The study involved undergraduate students from the University of Minnesota but did not assess a range in the skills of the subjects, as it was not required for the study’s objective. The objective was simply to evaluate how a repeated sequence or random sequence affected reaction times. To properly evaluate sequence learning as a model for skill acquisition, it would be beneficial to select a task that one could potentially become proficient in, such as playing the violin, including novice, advanced, and professional violinists. Evaluating a group of varying skills in a sequence learning task would highlight the limitations of the previous study.

Despite advancements in understanding sensorimotor control and skill acquisition in violin playing, a gap remains in the literature regarding coordination pattern reorganization in response to changes in instrument configuration, particularly in authentic performance settings. While some studies have explored how physical
alterations to the violin affect sensorimotor control and adaptation in skilled performers, few have explored how prior motor skills influence this adaptation process. Furthermore, most research has been conducted in controlled laboratory environments, limiting the generalizability of findings to real-world performance contexts.

This study aims to bridge this gap by investigating how violinists reorganize coordination patterns when faced with changes in instrument setup and how prior motor skills impact this adaptation process. Conducting experiments in authentic performance settings while maintaining rigorous methodologies and employing valid control groups will provide insights that can inform pedagogical practices in musical education and enhance my understanding of sensorimotor adaptation in violin performance. Through a comprehensive examination of coordination reorganization in response to altered instrument configurations, this study aims to significantly contribute to the existing body of knowledge in biomechanics and musical training.
III. METHODS

A. Participants

This study had two objectives: 1) to examine how patterns of coordinated movement acquired through years of study of violin performance - a real-world motor task - impact the subsequent reorganization of coordination in novel task variations that are "similar" to the original task to varying degrees; and 2) to determine the extent to which the reorganization of coordination patterns is impacted by baseline skill in the original task. I therefore established broad inclusion criteria for students and teachers of the violin, who might wish to participate in my study. Inclusion criteria included a minimum of two years of violin study such that a baseline level of skill should have been acquired, and a clearly stated desire to participate in the study.

One hundred healthy individuals (66 female, 34 male) were recruited to participate from attendees of the Music Institute of Chicago’s 2019 and 2022 Summer Suzuki Institutes. Participants spanned a wide range of ages (7 to 72 years), with a mean age of 21.9 ± 14.9 years. Participants also spanned a broad range of experience levels, from beginners with 2+ years of violin training to professional performers with decades of study. All subjects had normal or corrected-to-normal vision, and all were naïve to the purposes of the study. All participants provided written, informed consent (or assent plus parental consent) to participate in the experimental procedures of this study. All consenting and testing procedures received institutional review and approval in accordance with the Declaration of Helsinki (MU IRB 1806024918).
B. Setup

Each subject sat on a stool in front of an Optotrak 3020 motion capture system (Figure 7A; Northern Digital, Inc.). The Optotrak system collected marker position data in three-dimensional space (3D) at a rate of 100 samples per second from active infrared (IRED) markers mounted on a set of three full-sized violins and bows and a set of three half-sized violins and bows (Figure 7B). The Optotrak system was equipped with an Optotrak Data Acquisition Unit (ODAU), which I used to digitize two analog audio inputs at a rate of 10000 samples per second. One of the audio signals (from the violin) was transduced by either bridge-mounted pickups for the full-sized violins, or by a high-quality dynamic microphone (model SM57; Shure, Inc.) for the half-sized violins. The other audio signal (from a metronome) was transduced by a second dynamic microphone. The audio signals were pre-amplified (Xenyx-1002 mixer; Behringer, Inc.; Willich, Germany) to yield a full-scale dynamic range of approximately ±5V prior to sampling with a 12-bit resolution by the ODAU. This audio preprocessing ensured the ability to capture nuances in performance dynamics and articulation. During data collection, the Optotrak system maintained synchrony of the IRED marker data and analog audio signals.
Each set of three violins included a control violin with the standard string ordering and placement (i.e., string arrangement: G-D-A-E), a violin with inverted string ordering (i.e., E-A-D-G), and a violin with shuffled string ordering (i.e., A-G-E-D). I refer to these violins as the "control", "inverted" and "shuffled" violins, respectively (Figure 7C). The inverted violin is more similar to the control violin than the shuffled
violin, in the sense that the familiar nearest-neighbor relationships of the control violin strings are preserved for the inverted violin, but not for the shuffled violin. Each set of three violins was fitted by a professional luthier with custom bridges such that bridge curvature and string spacings were well-matched, thus ensuring a consistent "feel" of the violins within each set. Aside from string placements, each member in each set of violins was indistinguishable visually from the other members of the set.

Figure 8: One set of violins used in the experiment. The violins were set up by a professional Luthier to ensure consistent bridge curvature and string spacings within each set. Violins include (from left to right): control, inverted, and shuffled arrangements.
C. Experimental Procedures

Subjects participated in a single 20-minute experimental session wherein they were asked to play a short musical phrase - a two-octave G-Major arpeggio - repeatedly and with short, separated, marcato bowings (Figure 7C). I asked each subject to attempt 50 iterations of the 13-note G-major arpeggio (Figure 7D) to be played in first position "in time" with a metronome set to a rate of 140 beats per minute. Each iteration was considered a separate "trial," with a brief pause between trials. Subjects were instructed to initiate each trial when ready upon a verbal "GO" cue from the experimenter.

I utilized an "A-B-A format" experimental design wherein each participant served as their own internal control (Figure 7E). The first 10 trials were performed with a control violin with a standard string arrangement and were considered the practice (or baseline) block of trials; the next 30 trials were performed with a test violin and were considered the test block of trials; the final 10 trials were again performed with a control violin were considered the washout block of trials. All participants performed the trials with experimental violins closest in size to their personal violin. At the beginning of the test block of trials, each subject had the control violin taken from them and removed from their sight. After a brief pause of about 1 minute, participants received a new violin of appropriate size with instructions not to "explore" the violin prior to attempting the next arpeggio. Upon re-connecting the instrument to the data collection systems, participants commenced the test trials, which were intended to reveal the differential effects of two forms of string order manipulation on arpeggio performance. Although participants were told they could request a break at any time, none chose to do so. At the end of the test
block, each subject had their test violin taken from them and removed from sight. After another brief pause, participants received again the control violin with instructions not to explore it prior to attempting the next arpeggio. The final 10 trials were intended to reveal any aftereffects of string order manipulation on subsequent performance.

After the informed consent/assent process, participants were assigned without their knowledge into one of three test groups: shuffled, inverted, or control. During pilot testing, I observed that violinists typically performed arpeggios with great consistency when playing a violin with standard string ordering; I, therefore, used a group assignment approach that favored participant allocation to the two test groups with altered string arrangements over the control group in a 2:2:1 ratio (shuffled; inverted; control, respectively; see Table 1). Participants in the shuffled group received the shuffled violin during the test block of trials, participants in the inverted group received the inverted violin in the test block, and participants in the control group received the control violin again in the test block. Importantly, to compensate for the string order manipulations, subjects adapt several aspects of their performance including the bow angle relative to the body of the violin upon each note onset.

<table>
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<th>6-9</th>
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<td>6</td>
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</tr>
<tr>
<td>Shuffled</td>
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<tr>
<td>Number of Subjects per Skill</td>
<td>31</td>
<td>32</td>
<td>37</td>
</tr>
</tbody>
</table>
Upon completion of the experiment, each participant was asked to indicate the number of years they had studied violin, how many hours per week they currently practiced, and which Suzuki book they currently studied (a coarse but objective measure of acquired skill).
D. Data Analysis and Statistical Hypothesis Testing

My study had two experimental goals. The first sought to determine how well-learned patterns of coordinated movement are reorganized in novel task variations that are "similar" to the original task to varying degrees. The second sought to determine the extent to which the reorganization of coordination is impacted by baseline skill in the original task. I addressed these objectives by analyzing the audio signals and the bow movement kinematics recorded during testing.

Raw audio data from each trial were imported into the Matlab computing environment for post-processing (Matlab version 2023a; The MathWorks, Inc.; Natick MA). I applied an automated algorithm to the violin's audio signal from each trial performed by each participant to obtain note onset times for each note played. Cross-validation efforts found that the note onset detection algorithm had 99.20% sensitivity and 99.99% specificity relative to hand-coded note onset times. After automated processing, note onset times were plotted atop the raw audio data from each trial for visual inspection, and the onsets were manually adjusted where needed. From these data, I computed several performance variables that together, provide insight into the violinist's ability to perform the 13-note arpeggio in time with the metronome when exposed to the altered violins.

To assess performance accuracy, I calculated the number of notes attempted in each trial and the mean inter-note interval within each trial. I assessed performance variability using the standard deviation (SD) of inter-note intervals within each trial. If
the arpeggio is performed correctly, the violinist should play only 13 notes with an average inter-note interval of 0.43 seconds and low inter-note interval variability.

I analyzed bow kinematics to glean insight into how patterns of movement coordination are reorganized in response to two spatial manipulations of string arrangement on the violin, one of which was more "similar" to the task of playing a conventional violin than the other. To start, I used the raw marker data to attach two separate reference frames to the instrument: one fixed to the bow \( \{ \hat{x}_B, \hat{y}_B, \hat{z}_B \} \) with the - \( \hat{x}_B \) axis directed along the long axis of the bow, and a second fixed to the violin \( \{ \hat{x}_V, \hat{y}_V, \hat{z}_V \} \) with the \( \hat{y}_V \) axis directed along the strong toward the scroll (Figure 1, top). I used these fixed frames to compute two kinematic performance variables, which I used to characterize bow motions throughout each trial. I quantified the bow inclination angle \( \vartheta \) relative to the violin as in Equation 2 (Schoonderwalt et al. 2009; Figure 9). The inclination angle (also known as the attack angle) is typically associated with playing different strings. By convention, the inclination angle is considered positive when this angle moves from lower to higher-pitched strings.

I quantified the bow skew angle \( \varphi \) relative to the violin as in Equation 1 (Schoonderwalt et al. 2009; Figure 9). The skew angle describes deviations in the bowing direction from perpendicularity to the strings in the plane of the violin. By convention, the skew angle is considered positive when the frog is pointed farther away from the player's body.

**Figure 9:** The two angles used to assess the kinematics of bowing. Figure adapted from Schoonderwalt et al. (2009) with permission.
I computed three outcome measures based on these two bow angles. One of these measures - the *variability of attack angle residuals at note onset* - relates to how consistently the violinists oriented the bow relative to each string at the onset of each note. To derive this measure, I first computed the attack angle of the bow at each note onset (i.e., the onset inclination angle) by averaging the inclination angle within a 50 ms time window starting at the moment of note onset identified in my audio analysis. I then subtracted from each onset attack angle that subject's baseline onset inclination angle averaged - on a per-string basis - from baseline trials 8-10. (To make this work, the fundamental pitch of each played note was identified using Fourier analysis and used to infer the played string, which was uniquely defined by the note's fundamental frequency under the assumption that the violinists complied with our instructions to play the arpeggio in first position.) The resulting attack angle residuals correspond to variations in the attack angle at each note onset relative to the attack angles performed when playing the same note at the end of baseline practice. I regard this performance measure, the variability of attack angle residuals, as a direct measure of how well each violinist compensated for the altered string arrangement at the very onset of each played note. Failure to reduce this performance variable would result, at the very least, in the bow striking two strings at once (an undesirable performance event known as a "double stop").

I next defined the bow's pre-note *attack angle choppiness* as the standard deviation of the bow's inclination angle within a 100 ms time window just preceding the moment of note onset. The pre-note attack angle choppiness quantifies the extent to which the violinist anticipates their actual attack angle in the moments just before playing a note, therefore representing a kinematic measure of movement economy. Inefficient
performances have high values of attack angle choppiness, whereas efficient performances have low values of attack angle choppiness.

Finally, I computed the variability of the bow skew angle at note onset. The bow skew angle does not impact which note is played but rather only the quality of the note's sound. Expert violinists control skew angle to a much greater degree than novices (Konczak et al. 2009). As such, I regard the variability of bow skew angle at note onset as a secondary measure of bowing efficiency and skill. To derive this measure, I first computed the bow's skew angle at each note onset by averaging the skew angle within a 50 ms time window starting at the moment of note onset. I then calculated the variability (standard deviation) of the average bow skew angle across all note onsets within a given trial. Lower values of this performance measure correspond to more efficient and skillful bowing motions, whereas higher values of this variable correspond to less efficient and less skillful motions.

For each of the audio and kinematic performance measures, I assessed the impact of task similarity on the response to sudden reordering of the violin strings by analyzing subject performance in each of six separate trial windows: in the final 3 trials of the baseline block (trials 8-10); at the onset, middle, and end of training (trials 11-13, 24-26, and 38-40, respectively); and at the onset and end of the washout block (trials 41-43 and 48-50, respectively). I used this data to test the hypothesis that motor re-learning is significantly impacted by the degree of similarity between a well-learned task and a novel task.

To do so, I applied mixed model repeated measures ANOVA and Post Hoc Bonferroni t-test to the audio and kinematic outcome measures within each of the six trial
windows. After first verifying that performances did not differ significantly between the participant groups at baseline, I assessed the impact of task similarity on how violinists adapt their playing and movement kinematics to the sudden reordering of the violin strings by comparing across the three groups (a between-subjects factor) performances within the three epochs of the test block: initial, middle, and final test epoch (i.e., a within-subjects factor). I assessed the impact of similarity on the extent of re-learning by comparing changes in performance across groups from the three trial epochs in the test block. I then examined the effects of similarity on aftereffects of re-learning by comparing across groups’ average performance from the three trial epochs performed with the control violin at the end of the baseline, and the beginning and end of the washout block. Finally, I evaluated the influence of skill level (a second between-subjects factor) on performance and coordinated movement across all experimental conditions. This involved stratifying participants based on their Suzuki book levels and analyzing their performance outcomes. Additionally, I included terms in the ANOVA model that investigated potential interactions between skill level, task similarity, and trial epochs. Significance was set at a family-wise error rate of $\alpha = 0.05$. All analyses were performed with JASP Team. (2024). JASP (Version 0.18.3) [Computer software for macOS].
IV. RESULTS

Participant characteristics varied widely within the control, inverted, and shuffled groups such that the groups did not differ meaningfully in age, number of years of study, number of hours of practice per week, their highest level of formal Suzuki training, or their confidence in their ability to play a G-major arpeggio (Table 1). All of the research participants were observed to be attentive and engaged throughout their experimental session.

To illustrate the analysis of audio performance variables and measures of bow kinematics, Figure 10 depicts raw data from a control subject (trial 10), including audio voltage, audio frequency, attack angles, and skew angles. I addressed my study's two main objectives by analyzing how two sets of dependent measures (audio performance variables; measures of bow kinematics) vary as a function of participant group (control; inverted; shuffled) as a function of time (i.e., before, during, and after exposure to the test violins).

![Figure 10: Individual control subject’s trial 10 audio and bow kinematics raw data (note onsets: red dashed lines).]
Figure 11 presents a time series of raw audio data recorded from selected trials performed by a subject who attempted to play the inverted violin during test block trials. During the baseline block performed with the control violin, the subject demonstrated competence in performing the required 13-note arpeggio in time with a metronome set to 140 beats per minute. Onset times (red vertical lines) identified during the baseline trial (Fig 11, Baseline) were regularly spaced with a mean inter-note interval of 0.43 s. The subject’s performance was disrupted on initial exposure to the shuffled violin (Fig 11, Initial Test) in that the note count and the variability of note onset timing both increased. By the end of 30 trials of practice with the inverted violin, the subject had attained a level of performance rivaling that observed during baseline testing. I observed no apparent aftereffects of training with the inverted violin (Fig 11, Initial Washout) in that the number of notes and their onset timing were indistinguishable from baseline performance immediately after receiving the control violin once again.

Figure 11: Raw audio data (blue) with note onsets (red) plotted for trials 10 (baseline), 11 (initial test), 25 (middle test), 40 (final test), 41 (initial washout), and 50 (final washout) for an inverted subject.
A. Audio Performance Measures

Figure 12 plots mean values for the three audio performance measures as a function of the trial number for each of the three subject groups. Visual inspection of the plots suggests several notable trends. For all three dependent variables, performance approached ideal values by the end of baseline practice. Performance was degraded transiently on initial exposure to the test violin in the inverted and shuffled groups but not in the control group. Although performance improved throughout 30 training trials for the inverted and shuffled groups, baseline levels of performance had not been recovered by the end of test trials for these subjects. Transient aftereffects of exposure to the test violin were notable for participants subjected to the inverted violin but not the shuffled or control violins.

Figure 12: Cohort mean audio performance variables as a function of trial number for each of the three subject groups. All subjects played the G-Major arpeggio with the control violin on trials 1-10. Trials 11-40 were played using the test violin (control, inverted, shuffled). All subjects played trials 41-50 on the control violin. A) Mean number of notes played. B) Inter-note interval (ideal = 140 bpm). C) Inter-note interval variability. Shading: ±1 standard error of the mean (SEM). Grey vertical bands: Trial epochs analyzed statistically as presented in Figure 13.
Figure 13 plots individual participant mean values for each of the three audio performance variables in each of six trial epochs: at the end of baseline practice (trials 8-10), upon initial exposure to the test violins (trials 11-13); in the middle and at the end of exposure (trials 24-26 and trials 38-40, respectively), and at the beginning and end of the washout block of trials (trials 41-43 and 48-50, respectively). Although performance appeared to be quite similar for each of the three groups at the end of baseline practice, performance was disrupted during exposure to the inverted and shuffled violins. Exposure to the inverted violin appeared to have a persistent impact on the mean inter-note interval even after the control violin was returned to them.

These visual observations were corroborated with a pair of three-way,
mixed model, repeated measures ANOVA applied to each of the three dependent audio performance measures. Independent factors included two between-subjects factors (participant group, participant skill level) and one within-subjects factor (trial epoch). One analysis in each pair focused on the three trial epochs performed with the test violin (initial, middle, and test block epochs); the second in each pair compared performance with the control violin before (late baseline epoch) and after exposure to the test violin (initial and final washout epochs).

During exposure to the test violins, mixed model repeated measures ANOVA found a significant within-subjects main effect of trial epoch on all three dependent audio performance measures \( F_{(2,178)} > 4.96; p < 0.008 \) in each case, and a between-subjects main effect of participant group on the average number of notes played and on the mean inter-note interval \( F_{(2,89)} > 4.11; p < 0.020 \) in both cases. An interaction between the trial epoch and participant group reached statistical significance for just the mean inter-note interval \( F_{(4,178)} = 3.62; p = 0.007 \) (see Tables 2, 3, 4, and Figure 13).
Table 2: Mean Number of Notes Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>$\eta^2$</th>
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<td>7.858*10^-4</td>
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Note. Type III Sum of Squares
* Mauchly’s test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Between Subjects Effects ▼

<table>
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<tr>
<th>Cases</th>
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Note. Type III Sum of Squares

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).

Table 3: Mean Inter-Note Interval Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

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<td>0.010</td>
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</tr>
</tbody>
</table>

Note. Type III Sum of Squares
* Mauchly’s test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Between Subjects Effects ▼

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>$\eta^2$</th>
<th>$\eta^p_2$</th>
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<tr>
<td>Condition</td>
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<td>0.273</td>
<td>7.118</td>
<td>0.001</td>
<td>0.082</td>
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<tr>
<td>Skill</td>
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<td>2</td>
<td>0.089</td>
<td>2.325</td>
<td>0.104</td>
<td>0.027</td>
<td>0.050</td>
</tr>
<tr>
<td>Condition + Skill</td>
<td>0.110</td>
<td>4</td>
<td>0.027</td>
<td>0.714</td>
<td>0.585</td>
<td>0.016</td>
<td>0.031</td>
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<tr>
<td>Residuals</td>
<td>3.415</td>
<td>89</td>
<td>0.038</td>
<td></td>
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</table>

Note. Type III Sum of Squares

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).
The impact of violin string reordering on audio performance was transient. Post Hoc Bonferroni t-test found that the within-subjects main effect of the test trial epoch was due to the average performance measure on initial exposure to the test violin being impacted more than performance in the middle (t(99) > 2.62, p < 0.03 for average inter-note intervals and variability of the inter-note intervals) and at the end of the test blocks (t(99) > 2.83, p < 0.016 for all three performance measures). Average performances in the middle and at the end of the test blocks did not differ from each other in any case (t(99) < 1.11, p > 0.79 in each case) (Tables 5, 6, and 7). Violin string reordering had the greatest impact on the average number of notes played and on the mean inter-note interval. Post Hoc Bonferroni t-test found that the between-subjects main effect of the participant group was due to average performance values from the shuffled and inverted

<table>
<thead>
<tr>
<th>Table 4: Mean Inter-Note Interval Variability Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within Subjects Effects</td>
</tr>
<tr>
<td>Cases</td>
</tr>
<tr>
<td>--------</td>
</tr>
<tr>
<td>Test Trial Epochs</td>
</tr>
<tr>
<td>Test Trial Epochs + Condition</td>
</tr>
<tr>
<td>Test Trial Epochs + Skill</td>
</tr>
<tr>
<td>Test Trial Epochs + Condition + Skill</td>
</tr>
<tr>
<td>Residuals</td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares
* Mauchly’s test of sphericity indicates that the assumption of sphericity is violated (p < .05).

<table>
<thead>
<tr>
<th>Between Subjects Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cases</td>
</tr>
<tr>
<td>--------</td>
</tr>
<tr>
<td>Condition</td>
</tr>
<tr>
<td>Skill</td>
</tr>
<tr>
<td>Condition + Skill</td>
</tr>
<tr>
<td>Residuals</td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares
groups being markedly greater than performance values in the control group [control-inverted (t(58) = 3.77, p < 0.001), control-shuffled (t(56) = 2.65, p = 0.03)]. Average audio performance values did not differ between the inverted and shuffled groups in either case (t(80) = 1.39, p = 0.51 in each case) (Tables 5 and 6). The significant interaction between the trial epoch and participant group for mean inter-note interval resulted from the marked difference between initial and later performances with the two test violins with reordered string arrangements (t(99) > 4.87, p < 0.001 in each case) but not with the control violin (t(99) = 0.06, p = 1.00 in both cases).

Three separate mixed models repeated measures ANOVA failed to find any significant main or interaction effects for any of the three dependent audio performance measures across the three trial epochs performed with the control violins during baseline and washout testing (Tables 5, 6, and 7).

<table>
<thead>
<tr>
<th>Table 5: Mean Number of Notes Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results</th>
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</thead>
<tbody>
<tr>
<td><strong>Within Subjects Effects</strong></td>
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<tr>
<td>Cases</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>Control Violin Trial Epochs</td>
</tr>
<tr>
<td>Control Violin Trial Epochs × Condition</td>
</tr>
<tr>
<td>Residuals</td>
</tr>
</tbody>
</table>

* Mauchly’s test of sphericity indicates that the assumption of sphericity is violated (p < .05).

<p>| <strong>Between Subjects Effects</strong>                                    |</p>
<table>
<thead>
<tr>
<th>Cases</th>
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<th>df</th>
<th>Mean Square</th>
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<th>p</th>
<th>$\eta^2$</th>
<th>$\eta_G^2$</th>
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<tbody>
<tr>
<td>Condition</td>
<td>0.052</td>
<td>2</td>
<td>0.026</td>
<td>1.410</td>
<td>0.25</td>
<td>0.012</td>
<td>0.030</td>
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<tr>
<td>Skill</td>
<td>0.100</td>
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<td>0.050</td>
<td>2.677</td>
<td>0.07</td>
<td>0.024</td>
<td>0.056</td>
</tr>
<tr>
<td>Condition × Skill</td>
<td>0.065</td>
<td>4</td>
<td>0.016</td>
<td>0.877</td>
<td>0.48</td>
<td>0.016</td>
<td>0.033</td>
</tr>
<tr>
<td>Residuals</td>
<td>1.673</td>
<td>90</td>
<td>0.019</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

* Mauchly’s test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Control violin trial epochs include trials 8-10 (baseline), 41-43 (initial washout), and 48-50 (final washout).
Table 6: Mean Inter-Note Interval Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

Within Subjects Effects

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control Violin Trial Epochs</td>
<td>0.0002</td>
<td>2</td>
<td>8.487×10⁻⁴</td>
<td>0.806</td>
<td>0.451</td>
<td>0.003</td>
<td>0.009</td>
</tr>
<tr>
<td>Control Violin Trial Epochs + Condition</td>
<td>0.008</td>
<td>4</td>
<td>0.002</td>
<td>1.784</td>
<td>0.134</td>
<td>0.015</td>
<td>0.038</td>
</tr>
<tr>
<td>Control Violin Trial Epochs + Skill</td>
<td>8.629×10⁻⁴</td>
<td>4</td>
<td>2.157×10⁻⁴</td>
<td>0.203</td>
<td>0.936</td>
<td>0.002</td>
<td>0.005</td>
</tr>
<tr>
<td>Control Violin Trial Epochs + Condition + Skill</td>
<td>0.003</td>
<td>8</td>
<td>4.346×10⁻⁴</td>
<td>0.410</td>
<td>0.914</td>
<td>0.007</td>
<td>0.018</td>
</tr>
<tr>
<td>Residuals</td>
<td>0.191</td>
<td>180</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares
* Mauchly's test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Between Subjects Effects

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>0.010</td>
<td>2</td>
<td>1.530</td>
<td>0.222</td>
<td>0.019</td>
<td>0.033</td>
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<tr>
<td>Skill</td>
<td>4.519×10⁻⁴</td>
<td>2</td>
<td>2.260×10⁻⁴</td>
<td>0.072</td>
<td>0.931</td>
<td>0.002</td>
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<tr>
<td>Condition = Skill</td>
<td>0.000</td>
<td>4</td>
<td>0.001</td>
<td>0.460</td>
<td>0.765</td>
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<tr>
<td>Residuals</td>
<td>0.283</td>
<td>90</td>
<td>0.003</td>
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</tr>
</tbody>
</table>

Note. Type III Sum of Squares

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Control violin trial epochs include trials 8-10 (baseline), 41-43 (initial washout), and 48-50 (final washout).

Table 7: Mean Inter-Note Interval Variability Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

Within Subjects Effects

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control Violin Trial Epochs</td>
<td>3.406×10⁻⁴</td>
<td>2</td>
<td>1.703×10⁻⁴</td>
<td>0.173</td>
<td>0.842</td>
<td>0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Control Violin Trial Epochs + Condition</td>
<td>2.630×10⁻⁴</td>
<td>4</td>
<td>6.576×10⁻⁴</td>
<td>0.666</td>
<td>0.616</td>
<td>0.008</td>
<td>0.015</td>
</tr>
<tr>
<td>Control Violin Trial Epochs + Skill</td>
<td>1.701×10⁻⁴</td>
<td>4</td>
<td>4.251×10⁻⁴</td>
<td>0.431</td>
<td>0.716</td>
<td>0.003</td>
<td>0.009</td>
</tr>
<tr>
<td>Control Violin Trial Epochs + Condition + Skill</td>
<td>4.489×10⁻⁴</td>
<td>8</td>
<td>5.611×10⁻⁴</td>
<td>0.569</td>
<td>0.803</td>
<td>0.014</td>
<td>0.025</td>
</tr>
<tr>
<td>Residuals</td>
<td>0.002</td>
<td>180</td>
<td>9.867×10⁻⁶</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares
* Mauchly's test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Between Subjects Effects

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>1.203×10⁻¹</td>
<td>2</td>
<td>6.014×10⁻⁶</td>
<td>0.437</td>
<td>0.629</td>
<td>0.004</td>
<td>0.010</td>
</tr>
<tr>
<td>Skill</td>
<td>4.022×10⁻⁵</td>
<td>2</td>
<td>2.011×10⁻⁵</td>
<td>1.580</td>
<td>0.216</td>
<td>0.013</td>
<td>0.034</td>
</tr>
<tr>
<td>Condition = Skill</td>
<td>4.827×10⁻⁵</td>
<td>4</td>
<td>1.207×10⁻⁵</td>
<td>0.936</td>
<td>0.447</td>
<td>0.015</td>
<td>0.040</td>
</tr>
<tr>
<td>Residuals</td>
<td>0.001</td>
<td>90</td>
<td>1.289×10⁻⁵</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Control violin trial epochs include trials 8-10 (baseline), 41-43 (initial washout), and 48-50 (final washout).
B. Bow Kinematic Measures

Figure 14 plots mean values for the three bow kinematic performance measures as a function of trial number for each of the three subject groups. For all three dependent variables, performance attained stable values by the end of baseline practice. Attack angle variability about the played string and pre-note attack angle choppiness were impacted to different extents upon exposure to the test violin in the inverted and shuffled groups but not in the control group. These effects were persistent in the sense that performance did not appear to change markedly throughout the test blocks of trials. String re-ordering did not have a systematic impact on the variability of the bow skew angle.

Figure 15 plots individual participant mean values for each of the

![chart]

**Figure 14:** Cohort mean bow kinematic performance variables as a function of trial for each of the three subject groups. All subjects played the G-Major arpeggio with the control violin on trials 1-10. Trials 11-40 were played using the test violin (control, inverted, shuffled). All subjects played trials 41-50 on the control violin. A) Attack angle variability. B) Skew angle variability. C) Attack angle choppiness. Shading: ±1 standard error of the mean (SEM). Grey vertical bands: Trial epochs analyzed statistically as presented in Figure 15.
three bow kinematic performance variables in each of the six trial epochs. Whereas the impact of string re-ordering on audio performance was transient, its impact on bow kinematics appeared to be more long-lasting, at least for the shuffled group. These visual observations were corroborated with a pair of three-way, mixed model, repeated measures ANOVA applied to each of the three kinematic performance measures; one analysis in each pair focused on trial epochs performed with the test violin and the second focused on the three trial epochs performed with the control violin.

During exposure to the test violins, mixed model repeated measures ANOVA found a significant between-subjects main effect of the participant group on the variability of attack angle residuals (relative to baseline performance) at note onset \( F_{(2,91)} = 633.03; p < 0.001 \), and on the choppiness of the bow attack angle in

**Figure 15:** Individual participants mean bow kinematic performance variables for each of the three subject groups as a function of trial blocking (baseline: trials 8-10; initial test: trials 11-13; middle test: trials 24-26; final test: trials 38-40; initial washout: trials 41-43; final washout: trials 48-50). A) Attack angle variability. B) Skew angle variability. C) Attack angle choppiness. Within each group and epoch, the different symbols correspond to subjects with different skill levels. •: intermediate; •: advanced; •: expert.
the moments just preceding note onset \( F_{(2,91)} = 24.53; p < 0.001 \). For both of these
kinematic measures, the control group performance values were significantly less than
those of the shuffled group \( |t| \geq 3.01; p < 0.01 \). For the variability of attack angle
residuals at note onset, control group performance values also were significantly less than
those of the inverted group \( |t| \geq 4.69; p < 0.001 \); the difference in choppiness
between the control and inverted groups did not reach statistical significance. An
interaction between trial epoch and participant group also reached statistical significance
for both of these performance measures \( F_{(4,182)} > 6.26; p < 0.001 \) (see Tables 8, 9, 10,
and Figure 15). For both performance measures, values of the dependent variables on
initial exposure to the test violin were less than those observed at the end and/or in the
middle of the test blocks for the shuffled group but not the inverted or control groups
\( |t| \geq 4.89; p < 0.001 \). Thus, the impact of violin string reordering on the kinematics
of bowing was slower to develop and long-lasting. Finally, an interaction between the
participant group and skill reached statistical significance for just the variability of attack
angle residuals (relative to baseline performance) \( F_{(4,91)} > 3.90; p = 0.006 \) (see Tables 8,
9, 10, and Figure 15). Here, the expert violinists were more variable with their attack
angles than the intermediate violinists, but only when confronted with the shuffled test
violin.
### Table 8: Mean Attack Angle Variability Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Sum of Squares</th>
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<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>$\eta^2$</th>
<th>$\eta^2_{p}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test Trial Epochs</td>
<td>50.350*</td>
<td>2*</td>
<td>25.175*</td>
<td>2.343*</td>
<td>.099*</td>
<td>6.544×10^{-4}</td>
<td>.025</td>
</tr>
<tr>
<td>Test Trial Epochs + Condition</td>
<td>269.153*</td>
<td>4*</td>
<td>67.288*</td>
<td>6.264*</td>
<td>&lt; .001*</td>
<td>0.033</td>
<td>0.121</td>
</tr>
<tr>
<td>Test Trial Epochs + Skill</td>
<td>37.187*</td>
<td>4*</td>
<td>9.297*</td>
<td>0.865*</td>
<td>.486*</td>
<td>4.833×10^{-4}</td>
<td>.019</td>
</tr>
<tr>
<td>Test Trial Epochs + Condition + Skill</td>
<td>162.157*</td>
<td>8*</td>
<td>20.270*</td>
<td>1.887*</td>
<td>0.064*</td>
<td>0.002</td>
<td>0.077</td>
</tr>
<tr>
<td>Residuals</td>
<td>1955.172</td>
<td>182</td>
<td>10.743</td>
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<td></td>
</tr>
</tbody>
</table>

*Note. Type III Sum of Squares*

Mauchly’s test of sphericity indicates that the assumption of sphericity is violated ($p < .05$).

### Between Subjects Effects

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<tr>
<th>Conditions</th>
<th>Sum of Squares</th>
<th>df</th>
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<th>F</th>
<th>p</th>
<th>$\eta^2$</th>
<th>$\eta^2_{p}$</th>
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</thead>
<tbody>
<tr>
<td>Condition</td>
<td>68617.429</td>
<td>2</td>
<td>34308.714</td>
<td>633.029</td>
<td>&lt; .001</td>
<td>0.892</td>
<td>0.933</td>
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<tr>
<td>Skill</td>
<td>72.379</td>
<td>2</td>
<td>36.390</td>
<td>0.668</td>
<td>0.513</td>
<td>9.407×10^{-4}</td>
<td>0.014</td>
</tr>
<tr>
<td>Condition + Skill</td>
<td>844.787</td>
<td>4</td>
<td>211.197</td>
<td>3.897</td>
<td>0.006</td>
<td>0.011</td>
<td>0.146</td>
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<td>Residuals</td>
<td>4931.993</td>
<td>91</td>
<td>54.198</td>
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*Note. Type III Sum of Squares*

### Table 9: Mean Skew Angle Variability Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
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<tr>
<th>Conditions</th>
<th>Sum of Squares</th>
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<th>Mean Square</th>
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<th>p</th>
<th>$\eta^2$</th>
<th>$\eta^2_{p}$</th>
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</thead>
<tbody>
<tr>
<td>Test Trial Epochs</td>
<td>0.531*</td>
<td>2*</td>
<td>0.266*</td>
<td>1.354*</td>
<td>0.261*</td>
<td>0.002</td>
<td>0.015</td>
</tr>
<tr>
<td>Test Trial Epochs + Condition</td>
<td>0.882*</td>
<td>4*</td>
<td>0.221*</td>
<td>1.124*</td>
<td>0.346*</td>
<td>0.003</td>
<td>0.024</td>
</tr>
<tr>
<td>Test Trial Epochs + Skill</td>
<td>0.662*</td>
<td>4*</td>
<td>0.166*</td>
<td>0.844*</td>
<td>0.499*</td>
<td>0.003</td>
<td>0.018</td>
</tr>
<tr>
<td>Test Trial Epochs + Condition + Skill</td>
<td>3.068*</td>
<td>8*</td>
<td>0.384*</td>
<td>1.955*</td>
<td>0.055*</td>
<td>0.012</td>
<td>0.079</td>
</tr>
<tr>
<td>Residuals</td>
<td>35.711</td>
<td>182</td>
<td>0.196</td>
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<td></td>
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</tbody>
</table>

*Note. Type III Sum of Squares*

Mauchly’s test of sphericity indicates that the assumption of sphericity is violated ($p < .05$).

### Between Subjects Effects

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>$\eta^2$</th>
<th>$\eta^2_{p}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>10.036</td>
<td>2</td>
<td>5.018</td>
<td>2.611</td>
<td>0.079</td>
<td>0.038</td>
<td>0.054</td>
</tr>
<tr>
<td>Skill</td>
<td>27.366</td>
<td>2</td>
<td>13.683</td>
<td>7.121</td>
<td>0.001</td>
<td>0.104</td>
<td>0.135</td>
</tr>
<tr>
<td>Condition + Skill</td>
<td>9.725</td>
<td>4</td>
<td>2.431</td>
<td>1.265</td>
<td>0.289</td>
<td>0.037</td>
<td>0.053</td>
</tr>
<tr>
<td>Residuals</td>
<td>174.858</td>
<td>91</td>
<td>1.922</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note. Type III Sum of Squares*

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).
I observed no main effects of trial epoch or participant group, or any interaction between these two factors on the variability of the bow skew angle at note onset. I did however observe a main effect of participant skill on the variability of bow skew angle at note onset \[ F_{(2,91)} = 7.12; \ p = 0.001 \], whereby skew angle variability was greater in performances by the group of violinists with least skill (Intermediate group) relative to those with more skill [Intermediate-Advanced (t(61) = 3.40; \ p = 0.003), Intermediate-Expert (t(66) = 3.32; \ p = 0.004)]. Skew angle variability did not differ between the Advanced and Expert groups (t(67) = 0.24; \ p = 1.00).

Finally, I performed separate mixed model repeated measures ANOVA on the three bow kinematic performance measures across the three trial epochs performed with the control violins (Tables 11, 12, and 13). The variability of attack angle residuals at note onset was the only performance measure to exhibit a main effect of participant group.
[\text{F}(2,91) = 3.98; p = 0.022] or trial epoch [\text{F}(2,182) = 8.29; p < 0.001]. The group effect reflected the fact that the control group played with slightly lower attack angle variability values than the inverted group (ltl(58) = 2.76; p = 0.021). The within-subject epoch effect was due to performance values in the initial washout trials being greater than those either at the end of baseline practice (ltl(99) > 3.94; p < 0.001) or at the end of the washout block (ltl(99) > 2.85; p = 0.015). These ANOVA found no main effects of trial epoch or participant group, or any interaction between these two factors on skew angle variability or bow attack angle choppiness. By contrast, I again observed a main effect of participant skill on the variability of bow skew angle at note onset [\text{F}(2,91) = 5.65; p = 0.005], whereby skew angle variability was greater in the (Intermediate group) relative to the Advanced and Expert groups [Intermediate-Advanced (ltl(61) > 3.00; p = 0.01), Intermediate-Expert (ltl(66) = 2.98; p = 0.011)]. Skew angle variability did not differ between the Advanced and Expert groups (ltl(67) > 0.16; p = 1.00).
Table 11: Mean Attack Angle Variability Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Within Subjects Effects</th>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control Violin Trial Epochs</td>
<td>35.737</td>
<td>2</td>
<td>17.868</td>
<td>8.290</td>
<td>&lt; .001</td>
<td>0.009</td>
<td>0.083</td>
<td></td>
</tr>
<tr>
<td>Control Violin Trial Epochs × Condition</td>
<td>11.918</td>
<td>4</td>
<td>2.980</td>
<td>1.382</td>
<td>0.242</td>
<td>0.003</td>
<td>0.029</td>
<td></td>
</tr>
<tr>
<td>Control Violin Trial Epochs × Skill</td>
<td>12.387</td>
<td>4</td>
<td>3.097</td>
<td>1.417</td>
<td>0.224</td>
<td>0.003</td>
<td>0.031</td>
<td></td>
</tr>
<tr>
<td>Control Violin Trial Epochs × Condition × Skill</td>
<td>19.885</td>
<td>8</td>
<td>2.486</td>
<td>1.153</td>
<td>0.330</td>
<td>0.005</td>
<td>0.048</td>
<td></td>
</tr>
<tr>
<td>Residuals</td>
<td>392.261</td>
<td>182</td>
<td>2.155</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares

Between Subjects Effects

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>279.451</td>
<td>2</td>
<td>139.726</td>
<td>3.982</td>
<td>0.022</td>
<td>0.067</td>
<td>0.080</td>
</tr>
<tr>
<td>Skill</td>
<td>381.359</td>
<td>2</td>
<td>90.579</td>
<td>2.581</td>
<td>0.081</td>
<td>0.043</td>
<td>0.054</td>
</tr>
<tr>
<td>Condition × Skill</td>
<td>75.668</td>
<td>4</td>
<td>18.917</td>
<td>0.539</td>
<td>0.707</td>
<td>0.018</td>
<td>0.023</td>
</tr>
<tr>
<td>Residuals</td>
<td>3191.392</td>
<td>91</td>
<td>35.092</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Control violin trial epochs include trials 8-10 (baseline), 41-43 (initial washout), and 48-50 (final washout).

Table 12: Mean Skew Angle Variability Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Within Subjects Effects</th>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control Violin Trial Epochs</td>
<td>0.693*</td>
<td>2*</td>
<td>0.347*</td>
<td>2.518*</td>
<td>0.083*</td>
<td>0.003</td>
<td>0.027</td>
<td></td>
</tr>
<tr>
<td>Control Violin Trial Epochs × Condition</td>
<td>0.308*</td>
<td>4*</td>
<td>0.077*</td>
<td>0.559*</td>
<td>0.693*</td>
<td>0.001</td>
<td>0.012</td>
<td></td>
</tr>
<tr>
<td>Control Violin Trial Epochs × Skill</td>
<td>0.143*</td>
<td>4*</td>
<td>0.036*</td>
<td>0.260*</td>
<td>0.903*</td>
<td>5.630×10⁻⁴</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>Control Violin Trial Epochs × Condition × Skill</td>
<td>0.735*</td>
<td>8*</td>
<td>0.092*</td>
<td>0.668*</td>
<td>0.719*</td>
<td>0.003</td>
<td>0.029</td>
<td></td>
</tr>
<tr>
<td>Residuals</td>
<td>25.042</td>
<td>182</td>
<td>0.138</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares

* Mauchly's test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Between Subjects Effects

<table>
<thead>
<tr>
<th>Cases</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>ηp²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>10.644</td>
<td>2</td>
<td>5.322</td>
<td>2.659</td>
<td>0.075</td>
<td>0.042</td>
<td>0.055</td>
</tr>
<tr>
<td>Skill</td>
<td>22.613</td>
<td>2</td>
<td>11.306</td>
<td>5.649</td>
<td>0.005</td>
<td>0.089</td>
<td>0.110</td>
</tr>
<tr>
<td>Condition × Skill</td>
<td>11.650</td>
<td>4</td>
<td>2.913</td>
<td>1.455</td>
<td>0.222</td>
<td>0.046</td>
<td>0.060</td>
</tr>
<tr>
<td>Residuals</td>
<td>182.150</td>
<td>91</td>
<td>2.002</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Control violin trial epochs include trials 8-10 (baseline), 41-43 (initial washout), and 48-50 (final washout).
Table 13: Mean Attack Angle Choppiness Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>η²p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control Violin Trial Epochs</td>
<td>0.144*</td>
<td>2*</td>
<td>0.072*</td>
<td>1.260*</td>
<td>0.286*</td>
<td>0.003</td>
<td>0.014</td>
</tr>
<tr>
<td>Control Violin Trial Epochs * Condition</td>
<td>0.383*</td>
<td>4*</td>
<td>0.096*</td>
<td>1.671*</td>
<td>0.159*</td>
<td>0.007</td>
<td>0.035</td>
</tr>
<tr>
<td>Control Violin Trial Epochs * Skill</td>
<td>0.106*</td>
<td>4*</td>
<td>0.026*</td>
<td>0.461*</td>
<td>0.765*</td>
<td>0.002</td>
<td>0.010</td>
</tr>
<tr>
<td>Control Violin Trial Epochs * Condition * Skill</td>
<td>0.498*</td>
<td>8*</td>
<td>0.062*</td>
<td>1.085*</td>
<td>0.375*</td>
<td>0.009</td>
<td>0.046</td>
</tr>
<tr>
<td>Residuals</td>
<td>10.431</td>
<td>182</td>
<td>0.057</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares
* Mauchly’s test of sphericity indicates that the assumption of sphericity is violated (p < .05).

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>p</th>
<th>η²</th>
<th>η²p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition</td>
<td>0.673</td>
<td>2</td>
<td>0.336</td>
<td>0.767</td>
<td>0.468</td>
<td>0.012</td>
<td>0.017</td>
</tr>
<tr>
<td>Skill</td>
<td>0.598</td>
<td>2</td>
<td>0.299</td>
<td>0.681</td>
<td>0.509</td>
<td>0.011</td>
<td>0.015</td>
</tr>
<tr>
<td>Condition * Skill</td>
<td>3.244</td>
<td>4</td>
<td>0.811</td>
<td>1.948</td>
<td>0.126</td>
<td>0.058</td>
<td>0.075</td>
</tr>
<tr>
<td>Residuals</td>
<td>39.936</td>
<td>91</td>
<td>0.439</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Type III Sum of Squares

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Control violin trial epochs include trials 8-10 (baseline), 41-43 (initial washout), and 48-50 (final washout).
V. DISCUSSION

In this study, I investigated the immediate and lasting effects of manipulating the string arrangement of violins, including inverted and shuffled configurations, on the performance of violinists, utilizing both audio measures and assessments of bow kinematics. My objectives were twofold: to explore how learned movement patterns adapt to novel task variations and to assess the influence of baseline skill level on the reorganization of movement patterns in response to novel task variations. Participants were required to play the G-Major arpeggio at 140 bpm for 50 trials, with some subjects receiving a test violin with altered string arrangements [shuffled (disrupting geometric similarity) or inverted (preserving geometric similarity)] in the B block of an A-B-A experimental format. An Optotrac 3020 motion capture system was used to record 3D data, capturing movement patterns of both bow and violin with infrared markers. The motion capture system also recorded and digitized synchronous audio signals. The results of this study showed there was a transient effect on audio performance from re-ordering the violin strings; this effect decreased throughout the 30 test trials consistent with re-learning. Contrary to expectations established in a related lab-based study (Ranganathan et al. 2014), subjects relearned faster with the less similar violin (shuffled) compared to the more similar violin (inverted); additionally, there were after-effects on performance when subjects returned to the normal violin, but only after playing the inverted violin. By contrast, bow kinematics showed sustained disruption during the test block. I observed no after-effects of exposure to either form of test violin on bow kinematics in the washout block, where subjects were given again the normal violin.
Although our findings revealed transient disruptions in audio performance upon exposure to test violins with altered string arrangements followed by adaptation and improvement with continued practice, full recovery to baseline levels was not achieved by the end of the test block trials. Furthermore, aftereffects persisted during the washout block trials, suggesting that at least some of the movement reorganization was due to sensorimotor adaptation (and not solely strategic compensation). The sustained or escalating effects of violin string re-ordering on bowing kinematics, as depicted in Figures 14 and 15, stands in notable contrast to the outcomes observed for the audio performance variables illustrated in Figures 12 and 13. Specifically, differences were observed in the variability of attack angle residuals at note onset and the choppiness of bow attack angle preceding note onset between the control and shuffled groups, with the shuffled group exhibiting greater variability and less choppiness. No significant differences were found between the control and inverted groups. Additionally, skill level influenced the variability of bow skew angle at note onset, with greater variability observed in performances by violinists with lower skill levels. This discrepancy underscores the complexity of motor skill adaptation and highlights the importance of considering both audio performance and bowing kinematics when studying motor learning processes in complex tasks. Understanding these dynamics is crucial for refining our comprehension of motor learning processes and for gaining insights into the mechanisms underlying motor adaptation in complex motor tasks, ultimately informing practices in biomedical engineering.
A. Facilitation, Interference, and the Contextual Role of Geometric Similarity in Motor Re-Learning

This study builds upon the work of Ranganathan et al. (2014), which investigated the role of geometric similarity in motor adaptation. Ranganathan and colleagues examined how altering the similarity between the geometric features of training and test tasks influenced motor learning and adaptation. Specifically, they manipulated the orientation of a virtual hand cursor in a reaching task, creating geometrically similar or dissimilar conditions between the training and test tasks. Ranganathan et al. (2014) conducted their study to address fundamental questions about the mechanisms underlying motor adaptation and the influence of task similarity on motor coordination. By systematically varying the geometric similarity between training and test tasks, they aimed to elucidate whether geometrically similar conditions facilitated motor adaptation compared to dissimilar conditions. The authors found that geometrically similar conditions did indeed facilitate motor adaptation, leading to faster and more accurate performance compared to dissimilar conditions. This result supports their hypothesis that geometric similarity between training and test tasks aids motor adaptation by leveraging previously learned movement patterns.

In contrast to Ranganathan et al.'s focus on reaching tasks in a virtual environment, my study investigated the impact of manipulating violin string arrangement on violinists' performance in a real-world musical context. While Ranganathan et al. (2014) manipulated geometric similarity by altering visual feedback cues, I manipulated task similarity by rearranging the physical configuration of the violin strings, thereby altering the tactile and spatial feedback cues available to violinists. Our study aimed to
extend the findings of Ranganathan et al. (2014) by examining motor adaptation in a real-world motor task with rich sensory feedback requirements. I sought to explore whether the principles of motor adaptation observed in lab-based reaching tasks would generalize to the domain of violin performance, where precise coordination of bowing technique and note timing is paramount.

During the violin arpeggio task, audio performance and bow kinematics were compared across geometrically similar condition (control and inverted violins) and dissimilar condition (control and shuffled violins). Participants exposed to inverted violins, where geometric similarity was largely preserved despite string rearrangement, experienced transient disruptions in performance. Although initial adaptation challenges were present, violinists eventually achieved a level of performance approaching baseline levels. However, full recovery was not attained by the end of the test block trials, indicating persistent effects of the manipulation. Aftereffects of exposure to the inverted violins persisted during the washout block trials, suggesting lasting effects on motor coordination consistent with the compensatory effects of sensorimotor adaptation. Participants exposed to shuffled violins also exhibited disruptions in performance comparable to those in the inverted violin condition. While initial adaptation was hindered, participants gradually improved their performance over the course of the test trials. However, I found no evidence of aftereffects attributable to sensorimotor adaptation during the washout block trials, suggesting that the shuffled violin elicited predominantly strategic compensations. The difference in observed aftereffects with the two altered violins suggests that exposure to inverted and shuffled violins may have
differentially recruited sensorimotor and strategic compensations based on the preservation or disruption of geometric similarity to the familiar control violin.

This discrepancy also underscores the importance of considering the context-specific nature of motor adaptation processes. While Ranganathan et al. focused on reaching tasks in a virtual environment (participants wore a data glove equipped with sensors that controlled the cursor on the screen), our study explored motor adaptation in the domain of real-world musical performance, specifically violin playing. By explicitly manipulating the geometric similarity of the task through violin string arrangements, I gained insights into how sensory-motor mappings are affected in complex motor tasks, highlighting the nuanced interplay between task characteristics and motor adaptation dynamics.

Another potential explanation for the differing outcomes could be the complexity and specificity of the motor skills involved in violin performance. Unlike reaching tasks, which primarily rely on visual feedback, violin playing requires precise coordination of tactile, auditory, and proprioceptive feedback. Altering the physical configuration of the violin strings disrupts the familiar sensory-motor mappings that violinists rely on, leading to transient disruptions in performance. Moreover, the discrepancy underscores the intricate interplay between task similarity, sensory feedback, and motor adaptation. While geometric similarity facilitated motor adaptation in Ranganathan et al.'s study, the alteration of task similarity in our study introduced novel challenges that initially impeded performance. The discrepancy highlights the need for nuanced investigations into motor adaptation across diverse contexts, considering the specific sensory-motor requirements of each task.
B. The Role of Acquired Skill Level in Shaping the Reorganization of Motor Coordination

Konczak and colleagues (2009) conducted a comprehensive study to investigate how skill level influences bowing movements during violin performance. Using a multi-camera motion tracking system and reflective markers, they meticulously analyzed the intricate dynamics of arm motion in individuals ranging from novice to expert violinists. The study focused on participants from the Suzuki violin program, performing the universally taught piece "Twinkle, Twinkle, Little Star." The primary aim of their study was to understand how skill proficiency shapes motor coordination during violin performance. The Suzuki program's structured pedagogy provided a unique opportunity to examine skill-dependent variations in bowing gestures and violin displacement. By elucidating the biomechanical underpinnings of violin performance across skill levels, the study aimed to contribute to the understanding of motor learning processes in a real-world musical context. Konczak et al. (2009) observed significant differences in bow skew angles and shoulder/elbow joint angles across participants of varying skill levels. Specifically, they noted a reduction in skew angle variance and a tight coupling between shoulder and elbow motions among skilled violinists. This reduction in variability was associated with a suppression of sagittal shoulder motion, indicating an experience-dependent modulation of motor coordination dynamics.

In my study, I similarly found significant associations between skill level and bow skew angle variability. Our results confirmed that less skilled violinists exhibited greater skew angle variability compared to more skilled counterparts, echoing Konczak's
observations of skill-dependent variations in motor coordination. In addition to the observed associations between skill level and bow kinematic measures, further analysis revealed intriguing correlations between skill proficiency and audio performance variables. Specifically, skilled violinists demonstrated more consistent note onset times and lower variability in inter-note intervals compared to less skilled participants.

Furthermore, while Konczak et al. primarily concentrated on biomechanical analyses of bowing movements among skilled violinists, our study extended this research by investigating the impact of task variations, particularly alterations in violin string arrangement, on bow kinematics. I observed persistent effects of string re-ordering on bow kinematics, with notable differences in the responses of violinists across skill levels. Skilled violinists demonstrated more consistent and precise bowing movements in response to the test violins (inverted/shuffled), exhibiting lower variability in bow skew angle compared to less skilled counterparts. By contrast, expert violinists were more variable with their attack angles than intermediate violinists, but only when confronted with the shuffled test violin. I did not find any meaningful impact of skill on measures of audio performance or attack angle choppiness. These findings underscore the nuanced relationship between skill level and motor adaptation strategies, thereby refining Konczak's observations of skill-dependent constraints on sensorimotor coordination but not necessarily on the re-organization of sensorimotor coordination. The varying responses of violinists with different skill levels to changes in task demands highlight the importance of considering individual skill levels in studies of motor adaptation and coordination. These findings underscore the importance of considering skill proficiency
as a critical factor in motor learning and adaptation processes, with implications for both theoretical models of motor control and practical applications in skill acquisition.
C. Limitations and Future Directions

There are several limitations to this study that should be acknowledged. Firstly, the relatively small size of the control population may have limited the sensitivity of our ANOVA to interaction effects, thereby limiting the generalizability of our findings. Future studies with larger sample sizes could relieve these sensitivity concerns. Additionally, our study focused exclusively on violin performance, and the generalizability of our findings to other motor tasks remains to be explored. Future research could investigate the transferability of motor learning principles across different tasks and domains (For example, playing the cello involves sight-reading a novel piece of music, which may exhibit notational or biomechanical similarity to a previously learned piece).

Moreover, while our study provides valuable insights into the impact of skill level on kinematic measures during violin performance, future investigations could employ longitudinal designs to track individuals' motor development over time. Longitudinal studies would offer a more comprehensive understanding of how skill acquisition influences motor coordination dynamics, allowing researchers to discern patterns of motor adaptation and skill refinement across various stages of learning.

Furthermore, incorporating electromyography (EMG) into future studies could enhance our understanding of the neural mechanisms underlying motor adaptation in complex tasks like violin performance. EMG provides direct measures of muscle activity, offering insights into the activation patterns and coordination of muscles involved in violin playing. By combining kinematic analyses with EMG recordings, researchers can
elucidate the interplay between biomechanical factors and neural control mechanisms, advancing our understanding of motor learning processes in intricate motor tasks.

In conclusion, our study sheds light on the mechanisms underlying motor learning and adaptation in the context of violin performance. By examining both audio performance measures and bow kinematics, the understanding of how violinists adjust their bow movements in response to changes in string arrangement has been expanded.


Kelleher, L. K. (2013, December). *Biomechanical research on bowed string musicians a scoping study.*


**Table 14:** Post Hoc Test for Mean Number of Notes Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Test Trial Epochs</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P_{Tukey}</th>
<th>P_{Scheffe}</th>
<th>P_{Bonf}</th>
<th>P_{Holm}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Test</td>
<td>1.199</td>
<td>0.557</td>
<td>2.152</td>
<td>.</td>
<td>.</td>
<td>0.098</td>
<td>0.065</td>
</tr>
<tr>
<td>Middle Test</td>
<td>1.818</td>
<td>0.557</td>
<td>3.265</td>
<td>.</td>
<td>.</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>Final Test</td>
<td>0.620</td>
<td>0.557</td>
<td>1.113</td>
<td>.</td>
<td>.</td>
<td>0.802</td>
<td>0.267</td>
</tr>
</tbody>
</table>

**Note:** P-value adjusted for comparing a family of 3

**Note:** Tukey and Scheffe corrected \( p \)-values are not appropriate for repeated measures post-hoc tests (Maxwell, 1980; Field, 2012).

<table>
<thead>
<tr>
<th>Condition</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P_{Tukey}</th>
<th>P_{Scheffe}</th>
<th>P_{Bonf}</th>
<th>P_{Holm}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>−2.243</td>
<td>0.859</td>
<td>−2.674</td>
<td>0.024</td>
<td>0.032</td>
<td>0.027</td>
<td>0.027</td>
</tr>
<tr>
<td>Inverted</td>
<td>−2.262</td>
<td>0.854</td>
<td>−2.648</td>
<td>0.026</td>
<td>0.034</td>
<td>0.029</td>
<td>0.027</td>
</tr>
<tr>
<td>Shuffled</td>
<td>−0.018</td>
<td>0.629</td>
<td>−0.029</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.977</td>
</tr>
</tbody>
</table>

**Note:** P-value adjusted for comparing a family of 3

**Note:** Results are averaged over the levels of: Skill, Test Trial Epochs

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).
Table 15: Post Hoc Test for Mean Inter-Note Interval Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>( P_{\text{Tukey}} )</th>
<th>( P_{\text{Scheffe}} )</th>
<th>( P_{\text{Bonf}} )</th>
<th>( P_{\text{Holm}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Test</td>
<td>0.080</td>
<td>0.017</td>
<td>4.735</td>
<td>.</td>
<td>.</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Final Test</td>
<td>0.099</td>
<td>0.017</td>
<td>5.857</td>
<td>.</td>
<td>.</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Middle Test</td>
<td>0.019</td>
<td>0.017</td>
<td>1.122</td>
<td>.</td>
<td>.</td>
<td>0.790</td>
</tr>
</tbody>
</table>

Note. \( P \)-value adjusted for comparing a family of 3

Note. Results are averaged over the levels of: Condition, Skill

Note. Tukey and Scheffe corrected \( p \)-values are not appropriate for repeated measures post-hoc tests (Maxwell, 1980; Field, 2012).

<table>
<thead>
<tr>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>( P_{\text{Tukey}} )</th>
<th>( P_{\text{Scheffe}} )</th>
<th>( P_{\text{Bonf}} )</th>
<th>( P_{\text{Holm}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control, Initial Test</td>
<td>-0.218</td>
<td>0.043</td>
<td>-5.045</td>
<td>&lt; .001</td>
<td>0.002</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Initial Test</td>
<td>-0.183</td>
<td>0.044</td>
<td>-4.173</td>
<td>0.002</td>
<td>0.031</td>
<td>0.002</td>
</tr>
<tr>
<td>Control, Middle Test</td>
<td>0.001</td>
<td>0.038</td>
<td>0.029</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Shuffled, Middle Test</td>
<td>-0.107</td>
<td>0.043</td>
<td>-2.479</td>
<td>0.249</td>
<td>0.631</td>
<td>0.507</td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>0.002</td>
<td>0.038</td>
<td>0.062</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Shuffled, Final Test</td>
<td>-0.065</td>
<td>0.043</td>
<td>-1.507</td>
<td>0.811</td>
<td>0.971</td>
<td>1.000</td>
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<table>
<thead>
<tr>
<th>Mean Difference</th>
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<th>t</th>
<th>( P_{\text{Tukey}} )</th>
<th>( P_{\text{Scheffe}} )</th>
<th>( P_{\text{Bonf}} )</th>
<th>( P_{\text{Holm}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control, Middle Test</td>
<td>0.184</td>
<td>0.044</td>
<td>4.198</td>
<td>0.001</td>
<td>0.029</td>
<td>0.002</td>
</tr>
<tr>
<td>Shuffled, Middle Test</td>
<td>0.076</td>
<td>0.032</td>
<td>2.358</td>
<td>0.314</td>
<td>0.696</td>
<td>0.700</td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>0.127</td>
<td>0.024</td>
<td>5.253</td>
<td>&lt; .001</td>
<td>0.001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Final Test</td>
<td>0.186</td>
<td>0.044</td>
<td>4.226</td>
<td>0.001</td>
<td>0.027</td>
<td>0.001</td>
</tr>
<tr>
<td>Inverted, Initial Test</td>
<td>0.113</td>
<td>0.023</td>
<td>4.876</td>
<td>&lt; .001</td>
<td>0.004</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Initial Test</td>
<td>0.153</td>
<td>0.023</td>
<td>6.709</td>
<td>&lt; .001</td>
<td>0.001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Control, Middle Test</td>
<td>0.175</td>
<td>0.032</td>
<td>5.419</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Middle Test</td>
<td>0.184</td>
<td>0.044</td>
<td>4.198</td>
<td>0.001</td>
<td>0.029</td>
<td>0.002</td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>0.076</td>
<td>0.032</td>
<td>2.358</td>
<td>0.314</td>
<td>0.696</td>
<td>0.700</td>
</tr>
<tr>
<td>Shuffled, Final Test</td>
<td>0.127</td>
<td>0.024</td>
<td>5.253</td>
<td>&lt; .001</td>
<td>0.001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Inverted, Initial Test</td>
<td>0.113</td>
<td>0.023</td>
<td>4.876</td>
<td>&lt; .001</td>
<td>0.004</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Initial Test</td>
<td>0.153</td>
<td>0.023</td>
<td>6.709</td>
<td>&lt; .001</td>
<td>0.001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Control, Middle Test</td>
<td>0.175</td>
<td>0.032</td>
<td>5.419</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Middle Test</td>
<td>0.184</td>
<td>0.044</td>
<td>4.198</td>
<td>0.001</td>
<td>0.029</td>
<td>0.002</td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>0.076</td>
<td>0.032</td>
<td>2.358</td>
<td>0.314</td>
<td>0.696</td>
<td>0.700</td>
</tr>
<tr>
<td>Shuffled, Final Test</td>
<td>0.127</td>
<td>0.024</td>
<td>5.253</td>
<td>&lt; .001</td>
<td>0.001</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

Note. \( P \)-value adjusted for comparing a family of 3

Note. Results are averaged over the levels of: Skill

Note. Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).
Table 16: Post Hoc Test Mean Inter-Note Interval Variability Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th></th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P_{Tukey}</th>
<th>P_{Scheffe}</th>
<th>P_{Bonf}</th>
<th>P_{Holm}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Test</td>
<td>0.171</td>
<td>0.065</td>
<td>2.618</td>
<td>.</td>
<td>.</td>
<td>0.029</td>
<td>0.019</td>
</tr>
<tr>
<td>Final Test</td>
<td>0.184</td>
<td>0.065</td>
<td>2.826</td>
<td>.</td>
<td>.</td>
<td>0.016</td>
<td>0.016</td>
</tr>
<tr>
<td>Middle Test</td>
<td>0.014</td>
<td>0.065</td>
<td>0.208</td>
<td>.</td>
<td>.</td>
<td>1.000</td>
<td>0.836</td>
</tr>
</tbody>
</table>

*Note.* P-value adjusted for comparing a family of 3

*Note.* Results are averaged over the levels of: Condition, Skill

*Note.* Tukey and Scheffe corrected p-values are not appropriate for repeated measures post-hoc tests (Maxwell, 1980; Field, 2012).

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).
Table 17: Post Hoc Test for Mean Attack Angle Variability Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control, Initial Test</td>
<td>-7.107</td>
<td>1.464</td>
<td>-4.853</td>
<td>&lt; .001</td>
<td>0.004</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Initial Test</td>
<td>-33.994</td>
<td>1.480</td>
<td>-22.961</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Control, Middle Test</td>
<td>-0.446</td>
<td>1.137</td>
<td>-0.392</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Inverted, Middle Test</td>
<td>-6.202</td>
<td>1.464</td>
<td>-4.235</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Middle Test</td>
<td>-37.698</td>
<td>1.480</td>
<td>-25.463</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>-0.567</td>
<td>1.137</td>
<td>-0.499</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Inverted, Final Test</td>
<td>-5.131</td>
<td>1.464</td>
<td>-3.504</td>
<td>0.017</td>
<td>0.149</td>
<td>0.021</td>
<td>0.006</td>
</tr>
<tr>
<td>Shuffled, Final Test</td>
<td>-36.290</td>
<td>1.480</td>
<td>-24.512</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
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</table>

Inverted, Initial Test

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shuffled, Initial Test</td>
<td>-26.887</td>
<td>1.140</td>
<td>-23.585</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Control, Middle Test</td>
<td>6.661</td>
<td>1.464</td>
<td>4.549</td>
<td>&lt; .001</td>
<td>0.011</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Inverted, Middle Test</td>
<td>0.905</td>
<td>0.730</td>
<td>1.239</td>
<td>0.947</td>
<td>0.992</td>
<td>1.000</td>
<td>0.868</td>
</tr>
<tr>
<td>Shuffled, Middle Test</td>
<td>-30.592</td>
<td>1.140</td>
<td>-26.834</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>6.540</td>
<td>1.464</td>
<td>4.466</td>
<td>&lt; .001</td>
<td>0.014</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Inverted, Final Test</td>
<td>1.975</td>
<td>0.730</td>
<td>2.705</td>
<td>0.153</td>
<td>0.506</td>
<td>0.269</td>
<td>0.012</td>
</tr>
<tr>
<td>Shuffled, Final Test</td>
<td>-29.184</td>
<td>1.140</td>
<td>-25.599</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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Shuffled, Initial Test

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control, Middle Test</td>
<td>33.549</td>
<td>1.480</td>
<td>22.660</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Inverted, Middle Test</td>
<td>27.792</td>
<td>1.140</td>
<td>24.378</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Shuffled, Middle Test</td>
<td>-3.704</td>
<td>0.757</td>
<td>-4.801</td>
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<td>0.004</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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<td>33.427</td>
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<td>22.578</td>
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<td>&lt; .001</td>
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<td>28.863</td>
<td>1.140</td>
<td>25.317</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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<tr>
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<td>-2.296</td>
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<td>0.067</td>
<td>0.333</td>
<td>0.100</td>
<td>0.022</td>
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Control, Middle Test

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
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<td>-5.756</td>
<td>1.464</td>
<td>-3.931</td>
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<td>0.058</td>
<td>0.004</td>
<td>0.002</td>
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<td>1.480</td>
<td>-25.163</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>-0.122</td>
<td>1.137</td>
<td>-0.107</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
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<td>-4.686</td>
<td>1.464</td>
<td>-3.200</td>
<td>0.043</td>
<td>0.257</td>
<td>0.059</td>
<td>0.017</td>
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<td>-35.845</td>
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<td>-24.211</td>
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<td>&lt; .001</td>
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Inverted, Middle Test

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shuffled, Middle Test</td>
<td>-31.497</td>
<td>1.140</td>
<td>-27.628</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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<td>5.635</td>
<td>1.464</td>
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<td>0.027</td>
<td>0.001</td>
<td>&lt; .001</td>
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<td>1.070</td>
<td>0.730</td>
<td>1.466</td>
<td>0.870</td>
<td>0.975</td>
<td>1.000</td>
<td>0.722</td>
</tr>
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<td>Shuffled, Final Test</td>
<td>-30.088</td>
<td>1.140</td>
<td>-26.392</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
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</table>

Control, Final Test

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inverted, Final Test</td>
<td>-4.566</td>
<td>1.464</td>
<td>-3.127</td>
<td>0.054</td>
<td>0.294</td>
<td>0.078</td>
<td>0.019</td>
</tr>
<tr>
<td>Shuffled, Final Test</td>
<td>-35.723</td>
<td>1.480</td>
<td>-24.129</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

Inverted, Final Test

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shuffled, Final Test</td>
<td>-32.159</td>
<td>1.140</td>
<td>-24.333</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

Note: P-value adjusted for comparing a family of 36
Note: Results are averaged over the levels of: Skill

Post Hoc Comparisons – Condition

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>-5.809</td>
<td>1.239</td>
<td>-4.688</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
<tr>
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<td>-35.657</td>
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<td>&lt; .001</td>
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</table>

Inverted

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P&lt;key</th>
<th>P&lt;schefte</th>
<th>P&lt;bonf</th>
<th>P&lt;holm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shuffled</td>
<td>-29.848</td>
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<td>-30.938</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

Note: P-value adjusted for comparing a family of 3
Note: Results are averaged over the levels of: Skill, Test Trial Epochs

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).
### Table 18: Post Hoc Test for Mean Attack Angle Variability Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results Continued from Table 17

<table>
<thead>
<tr>
<th>Condition</th>
<th>Skill</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>Psukey</th>
<th>Pschef</th>
<th>Pbonf</th>
<th>Pholm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control, Intermediate</td>
<td>Inverted, Intermediate</td>
<td>-0.839</td>
<td>2.349</td>
<td>-2.911</td>
<td>0.100</td>
<td>0.399</td>
<td>0.163</td>
<td>0.062</td>
</tr>
<tr>
<td>Shuffled, Intermediate</td>
<td>-3.575</td>
<td>2.554</td>
<td>-12.754</td>
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<td>&lt; .001</td>
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</tr>
<tr>
<td>Control, Advanced</td>
<td>-0.996</td>
<td>2.744</td>
<td>-0.363</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
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</tr>
<tr>
<td>Inverted, Advanced</td>
<td>-5.607</td>
<td>2.482</td>
<td>-2.259</td>
<td>0.378</td>
<td>0.744</td>
<td>0.945</td>
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<tr>
<td>Shuffled, Advanced</td>
<td>-3.216</td>
<td>2.392</td>
<td>-14.724</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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</tr>
<tr>
<td>Control, Expert</td>
<td>0.895</td>
<td>2.603</td>
<td>0.344</td>
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<tr>
<td>Inverted, Expert</td>
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<td>2.430</td>
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<td>0.818</td>
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<td>-39.280</td>
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<td>-16.532</td>
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<td>&lt; .001</td>
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<tr>
<td>Inverted, Intermediate</td>
<td>-25.736</td>
<td>1.735</td>
<td>-14.832</td>
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<tr>
<td>Control, Advanced</td>
<td>5.844</td>
<td>2.004</td>
<td>2.916</td>
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<td>0.396</td>
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<tr>
<td>Inverted, Advanced</td>
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<td>0.758</td>
<td>0.998</td>
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<td>1.000</td>
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<td>Shuffled, Advanced</td>
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<td>1.486</td>
<td>-19.007</td>
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<tr>
<td>Control, Expert</td>
<td>7.734</td>
<td>1.806</td>
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<td>0.028</td>
<td>0.002</td>
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<td>Inverted, Expert</td>
<td>-7.575</td>
<td>1.547</td>
<td>1.136</td>
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<td>0.995</td>
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<td>Shuffled, Expert</td>
<td>-32.440</td>
<td>1.460</td>
<td>-22.213</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
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<tr>
<td>Shuffled, Intermediate</td>
<td>Control, Advanced</td>
<td>31.579</td>
<td>2.240</td>
<td>14.097</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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<tr>
<td>Inverted, Advanced</td>
<td>26.968</td>
<td>1.910</td>
<td>14.117</td>
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<tr>
<td>Shuffled, Advanced</td>
<td>-2.641</td>
<td>1.792</td>
<td>-1.474</td>
<td>0.865</td>
<td>0.974</td>
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<tr>
<td>Control, Expert</td>
<td>35.470</td>
<td>2.065</td>
<td>16.206</td>
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<tr>
<td>Inverted, Expert</td>
<td>27.493</td>
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<td>-6.705</td>
<td>1.771</td>
<td>-3.786</td>
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<td>0.089</td>
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<tr>
<td>Control, Advanced</td>
<td>Inverted, Advanced</td>
<td>-4.611</td>
<td>2.157</td>
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<td>0.455</td>
<td>0.799</td>
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<td>0.352</td>
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<td>-34.220</td>
<td>2.053</td>
<td>-16.667</td>
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<tr>
<td>Control, Expert</td>
<td>1.890</td>
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<td>0.824</td>
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<td>-1.948</td>
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<td>0.871</td>
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<td>Shuffled, Expert</td>
<td>-18.284</td>
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<td>&lt; .001</td>
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</tr>
<tr>
<td>Inverted, Advanced</td>
<td>Shuffled, Advanced</td>
<td>-29.609</td>
<td>1.687</td>
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<td>&lt; .001</td>
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<td>6.502</td>
<td>1.975</td>
<td>3.292</td>
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<td>0.277</td>
<td>0.051</td>
<td>0.023</td>
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<tr>
<td>Inverted, Expert</td>
<td>0.525</td>
<td>1.741</td>
<td>0.301</td>
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<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
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</tr>
<tr>
<td>Shuffled, Expert</td>
<td>-13.673</td>
<td>1.665</td>
<td>-20.927</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
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<tr>
<td>Control, Expert</td>
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<td>1.861</td>
<td>19.406</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
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</tr>
<tr>
<td>Inverted, Expert</td>
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<td>1.611</td>
<td>18.710</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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</tr>
<tr>
<td>Shuffled, Expert</td>
<td>-4.064</td>
<td>1.528</td>
<td>-2.660</td>
<td>0.177</td>
<td>0.533</td>
<td>0.332</td>
<td>0.111</td>
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</tr>
<tr>
<td>Control, Expert</td>
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<td>-5.977</td>
<td>1.910</td>
<td>-3.129</td>
<td>0.057</td>
<td>0.294</td>
<td>0.085</td>
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</tr>
<tr>
<td>Inverted, Expert</td>
<td>Shuffled, Expert</td>
<td>-34.198</td>
<td>1.587</td>
<td>-21.548</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

**Note:** P-value adjusted for comparing a family of 36

**Note:** Results are averaged over the levels of: Condition, Test Trial Epochs

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).

### Table 19: Post Hoc Test for Mean Skew Angle Variability Across Test Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Condition</th>
<th>Skill</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>Psukey</th>
<th>Pschef</th>
<th>Pbonf</th>
<th>Pholm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intermediate</td>
<td>Advanced</td>
<td>0.781</td>
<td>0.230</td>
<td>3.400</td>
<td>0.003</td>
<td>0.004</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>Expert</td>
<td>0.731</td>
<td>0.220</td>
<td>3.320</td>
<td>0.004</td>
<td>0.006</td>
<td>0.004</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td>Advanced</td>
<td>Expert</td>
<td>-0.050</td>
<td>0.205</td>
<td>-0.244</td>
<td>0.968</td>
<td>0.971</td>
<td>1.000</td>
<td>0.808</td>
</tr>
</tbody>
</table>

**Note:** P-value adjusted for comparing a family of 3

**Note:** Results are averaged over the levels of: Condition, Test Trial Epochs

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).
Table 20: Post Hoc Test for Mean Attack Angle Choppiness Across TestEpochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Post Hoc Comparisons – Test Trial Epochs</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>Pukey</th>
<th>Pshciff</th>
<th>P dull</th>
<th>Pfront</th>
<th>Pholm</th>
<th>Note</th>
<th>P-value adjusted for comparing a family of 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Test</td>
<td>-0.142</td>
<td>0.040</td>
<td>-3.563</td>
<td>.</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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<td>.</td>
<td>-0.142</td>
<td>-0.040</td>
</tr>
<tr>
<td>Final Test</td>
<td>-0.155</td>
<td>0.040</td>
<td>-3.878</td>
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<td>&lt; .001</td>
<td>&lt; .001</td>
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<td>.</td>
<td>-0.155</td>
<td>-0.040</td>
</tr>
<tr>
<td>Middle Test</td>
<td>-0.013</td>
<td>0.040</td>
<td>-0.316</td>
<td>.</td>
<td>1.000</td>
<td>0.753</td>
<td>.</td>
<td>.</td>
<td>-0.013</td>
<td>-0.040</td>
</tr>
</tbody>
</table>

Note. Results are averaged over the levels of: Condition, Skill
Note. Tukey and Scheffe corrected p-values are not appropriate for repeated measures post-hoc tests (Maxwell, 1980; Field, 2012).

<table>
<thead>
<tr>
<th>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</th>
<th>Post Hoc Comparisons – Condition</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>Pukey</th>
<th>Pshciff</th>
<th>P dull</th>
<th>Pfront</th>
<th>Pholm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Test</td>
<td>Inverted, Initial Test</td>
<td>0.594</td>
<td>0.118</td>
<td>1.643</td>
<td>0.779</td>
<td>0.950</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Final Test</td>
<td>Inverted, Initial Test</td>
<td>-0.047</td>
<td>0.119</td>
<td>-0.526</td>
<td>0.084</td>
<td>0.571</td>
<td>0.239</td>
<td>0.129</td>
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<tr>
<td>Middle Test</td>
<td>Inverted, Initial Test</td>
<td>-0.039</td>
<td>0.088</td>
<td>-0.434</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Initial Test</td>
<td>-0.233</td>
<td>0.118</td>
<td>-0.208</td>
<td>0.527</td>
<td>0.845</td>
<td>1.000</td>
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</tr>
<tr>
<td>Control, Initial Test</td>
<td>Inverted, Initial Test</td>
<td>0.658</td>
<td>0.092</td>
<td>-7.169</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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</tr>
<tr>
<td>Middle Test</td>
<td>Inverted, Initial Test</td>
<td>0.239</td>
<td>0.056</td>
<td>0.542</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Control, Initial Test</td>
<td>Inverted, Initial Test</td>
<td>0.031</td>
<td>0.056</td>
<td>0.542</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Control, Initial Test</td>
<td>0.034</td>
<td>0.056</td>
<td>0.608</td>
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<tr>
<td>Inverted, Final Test</td>
<td>Control, Initial Test</td>
<td>-0.693</td>
<td>0.092</td>
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<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>-0.241</td>
<td>0.118</td>
<td>-2.624</td>
<td>0.001</td>
<td>0.958</td>
<td>0.191</td>
<td>0.345</td>
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<tr>
<td>Middle Test</td>
<td>Inverted, Final Test</td>
<td>-0.233</td>
<td>0.118</td>
<td>-2.956</td>
<td>0.054</td>
<td>0.562</td>
<td>0.863</td>
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</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>0.031</td>
<td>0.056</td>
<td>0.542</td>
<td>1.000</td>
<td>1.000</td>
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</tr>
<tr>
<td>Control, Final Test</td>
<td>Inverted, Final Test</td>
<td>0.275</td>
<td>0.092</td>
<td>2.997</td>
<td>0.011</td>
<td>0.989</td>
<td>0.166</td>
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</tr>
<tr>
<td>Middle Test</td>
<td>Inverted, Final Test</td>
<td>-0.453</td>
<td>0.058</td>
<td>-7.744</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
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</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Control, Final Test</td>
<td>-0.263</td>
<td>0.118</td>
<td>-2.336</td>
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<td>0.866</td>
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<tr>
<td>Inverted, Final Test</td>
<td>Control, Final Test</td>
<td>-0.425</td>
<td>0.119</td>
<td>-3.565</td>
<td>0.014</td>
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</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>0.267</td>
<td>0.092</td>
<td>2.268</td>
<td>0.036</td>
<td>0.741</td>
<td>0.890</td>
<td>0.424</td>
<td></td>
</tr>
<tr>
<td>Middle Test</td>
<td>Inverted, Final Test</td>
<td>-0.453</td>
<td>0.057</td>
<td>2.997</td>
<td>0.011</td>
<td>0.989</td>
<td>0.166</td>
<td>0.378</td>
<td></td>
</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>-0.460</td>
<td>0.119</td>
<td>-3.863</td>
<td>0.005</td>
<td>0.069</td>
<td>0.006</td>
<td>0.004</td>
<td></td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>Inverted, Final Test</td>
<td>-0.688</td>
<td>0.092</td>
<td>-7.501</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td></td>
</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>0.004</td>
<td>0.056</td>
<td>0.067</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Middle Test</td>
<td>Inverted, Final Test</td>
<td>-0.724</td>
<td>0.092</td>
<td>-7.888</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td></td>
</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>0.419</td>
<td>0.092</td>
<td>3.154</td>
<td>0.003</td>
<td>0.014</td>
<td>0.016</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>Inverted, Final Test</td>
<td>0.055</td>
<td>0.011</td>
<td>3.154</td>
<td>0.003</td>
<td>0.014</td>
<td>0.016</td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>-0.035</td>
<td>0.058</td>
<td>-0.600</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>Middle Test</td>
<td>Inverted, Final Test</td>
<td>0.273</td>
<td>0.092</td>
<td>2.319</td>
<td>0.038</td>
<td>0.716</td>
<td>0.782</td>
<td>0.412</td>
<td></td>
</tr>
<tr>
<td>Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Test trial epochs include trials 11-13 (initial test), 24-26 (middle test), and 38-40 (final test).</td>
<td>Inverted, Final Test</td>
<td>-0.454</td>
<td>0.119</td>
<td>-3.812</td>
<td>0.006</td>
<td>0.078</td>
<td>0.007</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td>Control, Final Test</td>
<td>Inverted, Final Test</td>
<td>-0.727</td>
<td>0.092</td>
<td>-7.929</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td>&lt; .001</td>
<td></td>
</tr>
</tbody>
</table>

Note. Results are averaged over the levels of: Skill, Test Trial Epochs
Table 21: Post Hoc Test for Mean Attack Angle Variability Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Post Hoc Comparisons – Control Violin Trial Epochs</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P_{Tukey}</th>
<th>P_{Scheffe}</th>
<th>P_{Bonf}</th>
<th>P_{holm}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>Initial Washout</td>
<td>−0.912</td>
<td>0.231</td>
<td>−3.943</td>
<td>.</td>
<td>.</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Final Washout</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial Washout</td>
<td>Final Washout</td>
<td>0.660</td>
<td>0.231</td>
<td>2.852</td>
<td>.</td>
<td>0.015</td>
<td>0.010</td>
</tr>
</tbody>
</table>

Note. P-value adjusted for comparing a family of 3
Note. Results are averaged over the levels of: Condition, Skill
Note. Tukey and Scheffe corrected p-values are not appropriate for repeated measures post-hoc tests (Maxwell, 1980; Field, 2012).

Table 22: Post Hoc Test for Mean Skew Angle Variability Across Control Violin Epochs and Participant Groups: Three-Way Mixed Model ANOVA Results

<table>
<thead>
<tr>
<th>Post Hoc Comparisons – Skill</th>
<th>Mean Difference</th>
<th>SE</th>
<th>t</th>
<th>P_{Tukey}</th>
<th>P_{Scheffe}</th>
<th>P_{Bonf}</th>
<th>P_{holm}</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intermediate</td>
<td>Advanced</td>
<td>0.704</td>
<td>0.234</td>
<td>3.003</td>
<td>0.010</td>
<td>0.014</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>Expert</td>
<td>0.671</td>
<td>0.225</td>
<td>2.984</td>
<td>0.010</td>
<td>0.014</td>
<td>0.011</td>
</tr>
<tr>
<td>Advanced</td>
<td>Expert</td>
<td>−0.033</td>
<td>0.209</td>
<td>−0.159</td>
<td>0.986</td>
<td>0.987</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Note. P-value adjusted for comparing a family of 3
Note. Results are averaged over the levels of: Condition, Control Violin Trial Epochs

Conditions were controlled, shuffled, and inverted violins. Skills were intermediate, advanced, and expert. Control violin trial epochs include trials 8-10 (baseline), 41-43 (initial washout), and 48-50 (final washout).
APPENDIX B: DATA ANALYSIS SCRIPTS

I. PLOT SINGLE SUBJECT RAW DATA

%% Sarah Hayden
% January 17th, 2024
% The code reads audio data from binary files corresponding to different
% trials of violin performances and plots the voltage signal over time. The
% x-axis represents time in seconds, and the y-axis represents voltage in
% volts. Red vertical lines indicate the onset frames of detected notes.
%
% Additionally, the code computes pitch and yaw angles of the violin bow
% based on marker positions and generates corresponding plots. The pitch
% angles, which represent the angle between the bow and strings, are
% plotted against frame index. Similarly, yaw angles, representing the
% angle of the bow relative to the violin's scroll, are also plotted
% against frame index.
clc
clear all
close
dataFolderPath = '/Users/sarahhayden/Library/CloudStorage/OneDrive-
SharedLibraries-MarquetteUniversity/Violinn - Documents/violin project
2022/Devon Code/Data/VSubs/S5 - Note State Machine';
classFolderPath = '/Users/sarahhayden/Library/CloudStorage/OneDrive-
SharedLibraries-MarquetteUniversity/Violinn - Documents/violin project
2022/Devon Code/Classes';
addpath(classFolderPath);
load('S003I.mat')

%% Audio
[ndi_array] = open_ndi_bin_file ('v1#010.dat');
notes=VSub.Trials(1,10).NoteOnsetFrames;
figure
plot(ndi_array(:, 2));
hold on; % This keeps the current plot and allows us to add more elements to it
xlabel('Time (sec)');
ylabel('Voltage (V)');
%title('Audio Signal Over Time (S008C-Trial 10)');
xline(notes, 'r','LineWidth', 1.5);
hold off

[ndi_array] = open_ndi_bin_file ('v1#011.dat');
notes=VSub.Trials(1,11).NoteOnsetFrames;
figure
plot(ndi_array(:, 2));
hold on;
xlabel('Time (sec)');
ylabel('Voltage (V)');
xline(notes, 'r','LineWidth', 1.5);
hold off

[ndi_array] = open_ndi_bin_file ('v1#025.dat');
notes = VSub.Trials(1,25).NoteOnsetFrames;
figure
plot(ndi_array(:, 2));
hold on;
xlabel('Time (sec)');
ylabel('Voltage (V)');
xline(notes, 'r','LineWidth', 1.5);
hold off

[ndi_array] = open_ndi_bin_file("v1#040.dat");
notes = VSub.Trials(1,40).NoteOnsetFrames;
figure
plot(ndi_array(:, 2));
hold on;
xlabel('Time (sec)');
ylabel('Voltage (V)');
xline(notes, 'r','LineWidth', 1.5);
hold off

[ndi_array] = open_ndi_bin_file("v1#041.dat");
notes = VSub.Trials(1,41).NoteOnsetFrames;
figure
plot(ndi_array(:, 2));
hold on;
xlabel('Time (sec)');
ylabel('Voltage (V)');
xline(notes, 'r','LineWidth', 1.5);
hold off

[ndi_array] = open_ndi_bin_file("v1#050.dat");
notes = VSub.Trials(1,50).NoteOnsetFrames;
figure
plot(ndi_array(:, 2));
hold on;
xlabel('Time (sec)');
ylabel('Voltage (V)');
xline(notes, 'r','LineWidth', 1.5);
hold off

%% Spectrogram
[ndi_array, freq, frame_total] = open_ndi_bin_file('v1#010.dat');
figure;
spectrogram(ndi_array(:,2),2048,1024,2048,10000,'yaxis','psd');
hold on;

% Plot vertical lines at note onset times
xline([notes/10000], 'r', 'LineWidth', 1.5);

% Define the frequencies of the G major arpeggio notes
frequencies_Hz = [196, 247, 294, 392, 494, 587, 784, 587, 494, 392, 294, 247, 196]; % G2, B2, D3, G3, B3, D4, G4, B4, D5, G5, B5, D6, G6

% Convert frequencies to kHz
frequencies_kHz = frequencies_Hz / 1000; % Convert Hz to kHz

% Get the x-coordinates of the note onset lines
note_onsets_kHz = (notes / 10000); % Convert note onset times from samples to kHz
% Plot horizontal bands at the frequencies corresponding to the G major arpeggio notes between consecutive note onset lines
% Plot horizontal bands at the frequencies corresponding to the G major arpeggio notes between consecutive note onset lines
for i = 1:length(note_onsets_kHz)-1
    x = [note_onsets_kHz(i), note_onsets_kHz(i+1)];
    % Plot horizontal band for each note between consecutive note onset times
    y = [frequencies_kHz(i), frequencies_kHz(i)]; % Set y values for all notes
    hold on
    plot(x, y, 'r', 'LineWidth', 1); % Plot horizontal bands for all notes
end

ylim([0 1])
xlim([0 10])
hold off;

%% Plotting one Pitch Attack Angle and the Note Onsets
% % Plot pitch angles
figure;
plot(1:length(PitchAngles), PitchAngles, 'b', 'LineWidth', 1.5);
hold on;

% Plot vertical lines at modifiedNoteOnsets
xline(NoteOnsetsSamples, 'r', 'LineWidth', 1.5);

% Add labels and title
xlabel('Frame Index');
ylabel('Pitch Angles (deg)');
%title('Pitch Angles with Modified Note Onsets');

% Add a legend
%legend('Pitch Angles', 'Modified Note Onsets', 'Location', 'Best');

% Plot Attack angles
figure;
plot(1:length(YawAngles), YawAngles, 'b', 'LineWidth', 1.5);
hold on;

% Plot vertical lines at modifiedNoteOnsets
xline(NoteOnsetsSamples, 'r', 'LineWidth', 1.5);

% Add labels and title
xlabel('Frame Index');
ylabel('Yaw Angles (deg)');
%title('Pitch Angles with Note Onsets');

% Add a legend
%legend('Pitch Angles', 'Modified Note Onsets', 'Location', 'Best');

%% Devon Lantagne's Function
function [PitchAngles, YawAngles] = ComputeAttackAngles(obj, frames)
% Returns two Fx1 array of pitch and yaw angles between the bow and strings.
% First col are pitch angles and second col are yaw angles.
% frames is an optional input argument. Used to specify
% specific frames to shorten computation. If left blank,
% will use all frames.
% Assume the violinist is right-handed:
- pitch angles are negative when hitting G string; positive for E string, and zero for the bow parallel to the plane of the violin.
- yaw angles are zero when the bow is hitting the strings perpendicularly, positive if the bow tip is pointing toward the scroll, negative if pointing toward the violinist.

Violin normal vector is computed as the cross product between two vectors with a common point (defined by ViolinNormRefMarks).
Violin axial vector represents the strings and is used for yaw angles.
Bow vector is the line between the extremes of the bow (markers 7 (tip) and 10 (windings)).

```matlab
if nargin < 2
    frames = 1:obj.MarkerFrames;
end

% Preallocate output array
PitchAngles = NaN(length(frames), 1);
if nargout > 1
    YawAngles = NaN(length(frames), 1);
end

% For every frame
for OutIdx = 1:length(frames)
    frame = frames(OutIdx);
    % Collect points of interest. If any are NaN, return NaN angles.
    % Bow Line Points
%
    % disp(size(obj.Markers.Bow));
    % disp(frame);

    BP_W = obj.Markers.Bow{frame,'M10'}; % Handle (winding)
    BP_T = obj.Markers.Bow{frame,'M7'}; % Tip
    % Bow unit vector
    BowVector = BP_T - BP_W;
    if any(isnan(BowVector))
        % If we don't have a bow line, we can't compute anything further.
        continue
    end
    BowVector = BowVector / norm(BowVector);

    % Compute Pitch Angle

    % Violin Plane Points

    % Find unit vector normal to violin plane
    [~, ~, VP_N] = GetBasisVector(VP_Common, VP_Axial, VP_Perp);

    % Pitch Angle
    PitchAngles(OutIdx) = 90 - acosd( dot(BowVector, VP_N));

    % Yaw Angle
    if (nargout > 1) && obj.HasMarker('MS')
% Get Strings Points
VP_Tail = obj.Markers.Violin{frame, 'M5'};
VP_Scroll = obj.Markers.Violin{frame, 'M5'};

% Get strings unit vector
StringVector = VP_Scroll - VP_Tail;
StringVector = StringVector / norm(StringVector); % Normalize

YawAngles(OutIdx) = 90 - acosd(dot(BowVector, StringVector));
end
end
end

function [ndi_array, freq, frame_total] = open_ndi_bin_file(ndiFileName)
% function [ndi_array, freq, frame_total] = open_ndi_bin_file(ndiFileName)

% Try to open the file
fid = fopen(ndiFileName, 'r');
if fid == -1
    error('Failed to open the file: %s', ndiFileName);
end
try
% Read file contents
fread(fid, 1, 'char'); % 32
item_total = fread(fid, 1, 'short'); % items per frame
subitem_total = fread(fid, 1, 'short'); % subitems per frame
column_total = item_total * subitem_total;
frame_total = fread(fid, 1, 'int'); % number of frames
freq = fread(fid, 1, 'float'); % collection frame frequency
fread(fid, 60, 'char'=>char'); % user comments
fread(fid, 60, 'char'=>char'); % system comments
fread(fid, 30, 'char'=>char'); % file description
fread(fid, 1, 'short'); % cutoff filter frequency
fread(fid, 8, 'char'=>char'); % time of collection
fread(fid, 1, 'short'); % unused?
fread(fid, 8, 'char'=>char'); % date of collection
fread(fid, 73, 'char'); % extended header and
unused

ndi_array = ones(frame_total, column_total) .* NaN;
for frame_num = 1:frame_total
    for column_num = 1:column_total
        data = fread(fid, 1, 'float');
        if (data < -100000) % technically, it is EE EE EE EE or -3.697314e+28
            data = NaN;
        end
        ndi_array(frame_num, column_num) = data;
    end
end

catch ME
% Close the file if an error occurs
fclose(fid);
rethrow(ME);
end
% Close the file
fclose(fid);
end

%% GetBasisVector
% Starting from three different points, this function create an orthonormal
% triade of vectors. m_common, m_x and m_y must be three dimensional
% points in the space

function [v1, v2, v3] = GetBasisVector (m_common, m_x, m_y)
v1 = m_x - m_common;
v1 = v1 / VMag(v1);  % V1 is the primary 'X' dimension vector
v2 = m_y - m_common;
v2 = v2 / VMag(v2);
v3 = cross(v1, v2);  % V3 is the primary 'Z' dimension vector
v3 = v3 / VMag(v3);
v2 = cross(v3, v1);  % V2 is the primary 'Y' dimension vector
end

%% Vmag
% This function is used to evaluate the magnitude of a vector in a 3D space
% it requires a 1x3 or a 3x1 vector as input and gives a scalar value of
% the magnitude of the vector in input
function OutValue = VMag(ThreeVector)
    if length(ThreeVector) ~= 3
        error('Input vector must be a 3-vector')
    else
        OutValue = sqrt(sum(ThreeVector.^2));
    end
end
II. PLOTTING AUDIO PERFORMANCE MEASURES

%% Sarah Hayden
% December 12, 2023
% This MATLAB script begins by loading experimental data from a file.
% It then categorizes subjects into different experimental conditions based
% on their IDs. Subsequently, it calculates statistical measures such as
% the mean number of notes, inter-note intervals, variability in inter-note
% intervals over multiple trials for each experimental condition. These
% statistics
% are visualized through plots, showcasing trends and differences among
% experimental groups. Finally, the processed data is saved into new .mat
% files for future reference. In essence, the script conducts detailed
% analyses to discern how experimental conditions affect note detection
% and related parameters in the dataset.

clear all
close all
clc

load OutputTable20240117T2129.mat % Devon Lantagne code creates this table

Subj_all = MT.SubID(:); % Grab all subject IDs
Subj_cell = char(Subj_all);

% Extract the last character from each string in Subj_cell
GroupCodes = Subj_cell(:,end);

% Convert the cell array of characters to a character array
GroupCodesCell = char(GroupCodes);

% Filter data based on conditions
Subj_C = find(GroupCodesCell == 'C');
Subj_I = find(GroupCodesCell == 'I');
Subj_S = find(GroupCodesCell == 'S');

num_subj = length(Subj_all); % number of subjects
num_notes = NaN(num_subj,50);
note_intervals = NaN(num_subj,50);
note_interval_var = NaN(num_subj,50);

for ik=1:num_subj
    disp(['subject: ' num2str(ik)]);
    tot_trial = [1:50];
f=1;
    for j = find(~isnan(tot_trial))
        if tot_trial(j) == NaN
            eval(['num_notes(ik,f) = NaN;'])
            eval(['note_intervals(ik,f) = NaN;'])
            eval(['note_interval_var(ik,f) = NaN;'])
            eval(['err_trans(ik,f)= NaN;'])
            eval(['ok_trans(ik,f)= NaN;'])
        else
...
if j<10
    name = ['trial0',num2str(j)];
else
    name = ['trial',num2str(j)];
end
num_notes(ik,:) = MT{ik,111:160};
note_intervals(ik,:) = MT{ik, 11:60};
note_interval_var(ik,:) = MT{ik, 61:110};
end
f=f+1;
end

CONTROLS = find(GroupCodes == 'C');
INVERTEDS = find(GroupCodes == 'I');
SHUFFLEDS = find(GroupCodes == 'S');

%% num notes
figure
plot(nanmean(num_notes(CONTROLS,:)),'b')
hold on
y1=nanmean(num_notes(CONTROLS,:))+nanstd(num_notes(CONTROLS,:))/sqrt(length(CONTROLS));
y2=nanmean(num_notes(CONTROLS,:))-nanstd(num_notes(CONTROLS,:))/sqrt(length(CONTROLS));
x = [1:50, fliplr(1:50)];
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'b');
plot(nanmean(num_notes(INVERTEDS,:)),'r')
y1=nanmean(num_notes(INVERTEDS,:))+nanstd(num_notes(INVERTEDS,:))/sqrt(length(INVERTEDS));
y2=nanmean(num_notes(INVERTEDS,:))-nanstd(num_notes(INVERTEDS,:))/sqrt(length(INVERTEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'r');
plot(nanmean(num_notes(SHUFFLEDS,:)),'g')
y1=nanmean(num_notes(SHUFFLEDS,:))+nanstd(num_notes(SHUFFLEDS,:))/sqrt(length(SHUFFLEDS));
y2=nanmean(num_notes(SHUFFLEDS,:))-nanstd(num_notes(SHUFFLEDS,:))/sqrt(length(SHUFFLEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'g');
indx=36;
plot(indx*ones(size(CONTROLS)),num_notes(CONTROLS,indx),'b.','MarkerSize',4);

V = axis;
xline(10,V)
xline(40,V)
yline(13)
ylabel('Mean Number of Notes')
xlabel('Trial')
legend('Control', '', 'Inverted', '', 'Shuffled', '')
%% plot inter-note intervals
figure
plot(nanmean(note_intervals(CONTROLS,:)),'b')
hold on
y1=nanmean(note_intervals(CONTROLS,:)) + nanstd(note_intervals(CONTROLS,:))/sqrt(length(CONTROLS));
y2=nanmean(note_intervals(CONTROLS,:)) - nanstd(note_intervals(CONTROLS,:))/sqrt(length(CONTROLS));
x = [1:50, fliplr(1:50)];
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'b');

plot(nanmean(note_intervals(INVERTEDS,:)),'r')
y1=nanmean(note_intervals(INVERTEDS,:)) + nanstd(note_intervals(INVERTEDS,:))/sqrt(length(INVERTEDS));
y2=nanmean(note_intervals(INVERTEDS,:)) - nanstd(note_intervals(INVERTEDS,:))/sqrt(length(INVERTEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'r');

plot(nanmean(note_intervals(SHUFFLEDS,:)),'g')
y1=nanmean(note_intervals(SHUFFLEDS,:)) + nanstd(note_intervals(SHUFFLEDS,:))/sqrt(length(SHUFFLEDS));
y2=nanmean(note_intervals(SHUFFLEDS,:)) - nanstd(note_intervals(SHUFFLEDS,:))/sqrt(length(SHUFFLEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'g');

V = axis;
xline(10,V)
xline(40,V)
ylabel('Inter-Note Interval (sec)')
xlabel('Trial')
legend('Control', 'Inverted', 'Shuffled', '')

%% plot inter-note intervals var
figure
plot(nanmean(note_interval_var(CONTROLS,:)),'b')
hold on
y1=nanmean(note_interval_var(CONTROLS,:)) + nanstd(note_interval_var(CONTROLS,:))/sqrt(length(CONTROLS));
y2=nanmean(note_interval_var(CONTROLS,:)) - nanstd(note_interval_var(CONTROLS,:))/sqrt(length(CONTROLS));
x = [1:50, fliplr(1:50)];
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'b');

plot(nanmean(note_interval_var(INVERTEDS,:)),'r')
y1=nanmean(note_interval_var(INVERTEDS,:)) + nanstd(note_interval_var(INVERTEDS,:))/sqrt(length(INVERTEDS));
y2=nanmean(note_interval_var(INVERTEDS,:)) - nanstd(note_interval_var(INVERTEDS,:))/sqrt(length(INVERTEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'r');

plot(nanmean(note_interval_var(SHUFFLEDS,:)),'g')
y1=nanmean(note_interval_var(SHUFFLEDS,:)) + nanstd(note_interval_var(SHUFFLEDS,:))/sqrt(length(SHUFFLEDS));
y2=nanmean(note_interval_var(SHUFFLEDS,:)) - nanstd(note_interval_var(SHUFFLEDS,:))/sqrt(length(SHUFFLEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'g');

V = axis;
xline(10,V)
xline(40,V)
ylabel('Note Interval Variability (sec)')
xlabel('Trial')
legend('Control', '', 'Inverted', '', 'Shuffled', '')

%% EPOCS
GroupCodes = num2cell(GroupCodes);

% Define trial blocks
trial_blocks = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
variable_xaxis = {'Number of Notes', 'Note Intervals', 'Note Interval Variability', 'Error Transition Probability', 'Ok-Transition Probability'};
% Define colors for different conditions
colors = {'b', 'r', 'g'};

% Define indices for grouping and variable arrays
groups = {8:10, 11:13, 24:26, 38:40, 41:43, 48:50};
variable_arrays = {num_notes, note_intervals, note_interval_var};
variable_names = {'num_notes', 'note_intervals', 'note_interval_var'};

% Iterate over variable arrays
for var_idx = 1:length(variable_arrays)
    % Initialize array to store average values for each trial block
    new_variable_array = zeros(size(variable_arrays{var_idx}, 1), length(groups));

    % Iterate over groups
    for group_idx = 1:length(groups)
        % Extract data for the current group
        data = variable_arrays{var_idx}(:, groups{group_idx});

        % Take the average of the columns and store in the new variable array
        new_variable_array(:, group_idx) = mean(data, 2);
    end

    % Store the new variable array with a dynamically generated name
    new_var_name = [variable_names{var_idx} '_new'];
    new_variable_array = [cellstr(Subj_all), GroupCodes, num2cell(new_variable_array)];
    new_variable_arrays{var_idx} = new_variable_array;

    % Assign the new variable array to the workspace
    assignin('base', new_var_name, new_variable_array);
end
save('num_notes_new.mat', 'num_notes_new');
save('note_intervals_new.mat', 'note_intervals_new');
save('note_interval_var_new.mat', 'note_interval_var_new');

%%
function xline (xlocation, V)
hold on
% V = axis;
plot(xlocation*[1 1], V(3:4),'k--')
return
function yline (ylocation)
hold on
V = axis;
plot (V(1:2), ylocation*[1 1],'k--')
return
end
III. BOW KINEMATICS CALCULATOR PER NOTE ONSET

%% Sarah Hayden
% August 11th, 2023
% This MATLAB code processes data from violin performance trials to compute various angles related to the bowing technique. It loads trial data stored in '.mat' files, extracts information about the violinist's actions, and calculates parameters such as pitch angles, yaw angles, average attack angles, standard deviation of yaw angles, and smooth angle for each note onset during the performance. The code iterates through the trials, extracting relevant data, performing calculations, and storing the results. Finally, it organizes the collected data into a table and saves it in a '.mat' file named 'Sarah_Hayden_NewAngles.mat'. Additionally, the code includes several utility functions for processing NDI bin files, computing basis vectors, and calculating vector magnitudes. The output is a table containing information about the analyzed violin performances, including the calculated angles and related parameters for each note onset. % Output table has 70038 rows with columns for different variables. % Please note, ‘smooth’ variable is our ‘choppiness’ variable

clc
close all
clear
dataFolderPath = '/Users/sarahhayden/Library/CloudStorage/OneDrive-SharedLibraries-MarquetteUniversity/Violinn - Documents/violin project 2022/Devon Code/Data/VSubs/S5 - Note State Machine';
classFolderPath = '/Users/sarahhayden/Library/CloudStorage/OneDrive-SharedLibraries-MarquetteUniversity/Violinn - Documents/violin project 2022/Devon Code/Classes';
addpath(classFolderPath);
matFiles = dir(fullfile(dataFolderPath, '*.mat'));
AttackAngleData = {};
% Initialize empty array for storing attack angle data

for fileIdx = 1:length(matFiles)  
currentFileName = fullfile(dataFolderPath, matFiles(fileIdx).name);
load(currentFileName, 'VSub');
subID = VSub.SubID;
conditionName = VSub.ConditionName;

ndiFolderPath = fullfile('/Users/sarahhayden/Library/CloudStorage/OneDrive-SharedLibraries-MarquetteUniversity/Violinn - Documents/violin project 2022/Devon Code/Data/OptoTrackData', subID);
umTrials = length(VSub.Trials);

for trialIdx = 1:numTrials  
currentTrial = VSub.Trials(trialIdx);

% Get frequency
firstTrialFileName = fullfile(ndiFolderPath, sprintf('c#%03d.dat', 1));
[freq, ~] = open_ndi_bin_file(firstTrialFileName);

=> [PitchAngles, YawAngles] = ComputeAttackAngles(currentTrial, 1:size(currentTrial.Markers, 1));
% Extract note onset times
NoteOnsetsTime = currentTrial.NoteOnsets;
NoteOnsetsSamples = round(NoteOnsetsTime * freq); % Use round to get integer indices

% Loop through note onsets
for onsetIdx = 1:length(NoteOnsetsSamples)
    currentOnsetFrame = NoteOnsetsSamples(onsetIdx);
    % Create pre note window for smooth variable calculation
    PreNoteWindow = (max(currentOnsetFrame - 9, 1):currentOnsetFrame);
    % Check if PreNoteWindow exceeds array bounds
    if any(PreNoteWindow <= 0) || any(PreNoteWindow > length(PitchAngles))
        fprintf('Subject %s, Trial %d, Onset %d: PreNoteWindow exceeds array bounds. Padding with NaN.
', subID, trialIdx, onsetIdx);
        PreNoteWindow(outOfBoundsIdx) = NaN;
    end
    % Calculate smooth variable
    validIndices = 1:length(PitchAngles);
    indicesToUse = intersect(PreNoteWindow, validIndices);
    AnglesPerOnset = PitchAngles(indicesToUse);
    % Check for NaNs in AnglesPerOnset
    if any(isnan(AnglesPerOnset))
        fprintf('Subject %s, Trial %d, Onset %d: AnglesPerOnset contains NaN. Calculating mean without NaN.
', subID, trialIdx, onsetIdx);
        smoothAngle = nanstd(AnglesPerOnset);
    else
        smoothAngle = nanstd(AnglesPerOnset);
    end
    % Create post note window for attack and yaw angle calculation
    PostNoteWindow = (currentOnsetFrame:min(currentOnsetFrame + 4, length(PitchAngles)));
    % Check if PostNoteWindow exceeds array bounds
    if any(PostNoteWindow <= 0) || any(PostNoteWindow > length(PitchAngles))
        fprintf('Subject %s, Trial %d, Onset %d: PostNoteWindow exceeds array bounds. Padding with NaN.
', subID, trialIdx, onsetIdx);
        PostNoteWindow(outOfBoundsIdx) = NaN;
    end
    % Calculate average attack angle
    validIndices = 1:length(PitchAngles);
    indicesToUse = intersect(PostNoteWindow, validIndices);
    AttackAnglesPerOnset = PitchAngles(indicesToUse);
    % Check for NaNs in AttackAnglesPerOnset
    if any(isnan(AttackAnglesPerOnset))
        fprintf('Subject %s, Trial %d, Onset %d: AttackAnglesPerOnset contains NaN. Calculating mean without NaN.
', subID, trialIdx, onsetIdx);
        avgAttackAngle = nanmean(AttackAnglesPerOnset);
    else
        avgAttackAngle = nanmean(AttackAnglesPerOnset);
    end
else
    avgAttackAngle = mean(AttackAnglesPerOnset);
end

% Calculate average yaw angle
validIndices = 1:length(YawAngles);
indicesToUse = intersect(PostNoteWindow, validIndices);
YawAnglesPerOnset = YawAngles(indicesToUse);

% Check for NaNs in YawAnglesPerOnset
if any(isnan(YawAnglesPerOnset))
    fprintf('Subject %s, Trial %d, Onset %d: YawAnglesPerOnset contains NaN. Calculating mean without NaN.\n', subID, trialIdx, onsetIdx);
    avgYawAngle = nanmean(YawAnglesPerOnset);
else
    avgYawAngle = mean(YawAnglesPerOnset);
end

% Calculate std yaw angle
validIndices = 1:length(YawAngles);
indicesToUse = intersect(PostNoteWindow, validIndices);
YawAnglesPerOnset = YawAngles(indicesToUse);

% Check for NaNs in YawAnglesPerOnset
if any(isnan(YawAnglesPerOnset))
    fprintf('Subject %s, Trial %d, Onset %d: YawAnglesPerOnset contains NaN. Calculating mean without NaN.\n', subID, trialIdx, onsetIdx);
    stdYawAngle = nanstd(YawAnglesPerOnset);
else
    stdYawAngle = nanstd(YawAnglesPerOnset);
end

% Store data in array
AttackAngleData = [AttackAngleData; {subID, conditionName, trialIdx, onsetIdx, avgAttackAngle, avgYawAngle, stdYawAngle, smoothAngle}];
end
end

fprintf('Analysis for Subject %s completed.\n', subID);

AttackAngleDataTable = cell2table(AttackAngleData, 'VariableNames', {'SubID', 'Condition', 'TrialNum', 'OnsetNum', 'avgAttackAngles', 'avgYawAngle', 'stdYawAngle', 'smoothAngle'});

% Save data in .mat file
save('Sarah_Hayden_NewAngles.mat', 'AttackAngleDataTable');
- yaw angles are zero when the bow is hitting the strings perpendicularly, positive if the bow tip is pointing toward the scroll, negative if pointing toward the violinist.

Violin normal vector is computed as the cross product between two vectors with a common point (defined by ViolinNormRefMarks).

Violin axial vector represents the strings and is used for yaw angles.

Bow vector is the line between the extremes of the bow (markers 7 (tip) and 10 (windings)).

```matlab
if nargin < 2
    frames = 1:obj.MarkerFrames;
end

% Preallocate output array
PitchAngles = NaN(length(frames), 1);
if nargout > 1
    YawAngles = NaN(length(frames), 1);
end

% For every frame
for OutIdx = 1:length(frames)
    frame = frames(OutIdx);
    % Collect points of interest. If any are NaN, return NaN angles.
    % Bow Line Points
    % disp(size(obj.Markers.Bow));
    % disp(frame);
    BP_W = obj.Markers.Bow{frame, 'M10'}; % Handle (winding)
    BP_T = obj.Markers.Bow{frame, 'M7'}; % Tip
    % Bow unit vector
    BowVector = BP_T - BP_W;
    if any(isnan(BowVector))
        % If we don't have a bow line, we can't compute anything further.
        continue
    end
    BowVector = BowVector / norm(BowVector);

    % Compute Pitch Angle
    % Violin Plane Points

    % Find unit vector normal to violin plane
    [~,~, VP_N] = GetBasisVector(VP_Common, VP_Axial, VP_Perp);

    % Pitch Angle
    PitchAngles(OutIdx) = 90 - acosd(dot(BowVector, VP_N));

    % Yaw Angle
    if (nargout > 1) && obj.HasMarker('MS')
        % Get Strings Points
        VP_Tail = obj.Markers.Violin{frame, 'M5'};
    end
```
VP_Scroll = obj.Markers.Violin{frame, 'MS'};

% Get strings unit vector
StringVector = VP_Scroll - VP_Tail;
StringVector = StringVector / norm(StringVector); % Normalize

YawAngles(OutIdx) = 90 - acosd( dot(BowVector, StringVector));

function [freq, frame_total] = open_ndi_bin_file(ndiFileName)
    % function [ndi_array, freq, frame_total] = open_ndi_bin_file(ndiFileName)

    % Try to open the file
    fid = fopen(ndiFileName, 'r');
    if fid == -1
        error('Failed to open the file: %s', ndiFileName);
    end

    try
        % Read file contents
        fread(fid, 1, 'char'); % 32
        item_total = fread(fid, 1, 'short'); % items per frame
        subitem_total = fread(fid, 1, 'short'); % subitems per frame
        column_total = item_total * subitem_total; % number of frames
        frame_total = fread(fid, 1, 'int'); % collection frame
        freq = fread(fid, 1, 'float'); % collection frame

        frequency
        fread(fid, 60, 'char=>char'); % user comments
        fread(fid, 60, 'char=>char'); % system comments
        fread(fid, 30, 'char=>char'); % file description
        fread(fid, 1, 'short'); % cutoff filter frequency
        fread(fid, 8, 'char=>char'); % time of collection
        fread(fid, 1, 'short'); % unused?
        fread(fid, 8, 'char=>char'); % date of collection
        fread(fid, 73, 'char'); % extended header and

        unused
        ndi_array = ones(frame_total, column_total) .* NaN;

        for frame_num = 1:frame_total
            for column_num = 1:column_total
                data = fread(fid, 1, 'float');
                if (data < -100000) % technically, it is EE EE EE EE or -
                    data = NaN;
                end
                ndi_array(frame_num, column_num) = data;
            end
        end
    catch ME
        % Close the file if an error occurs
        fclose(fid);
        rethrow(ME);
    end

    % Close the file
    fclose(fid);
function [v1, v2, v3] = GetBasisVector (m_common, m_x, m_y)
    v1 = m_x - m_common;
    v1 = v1 / VMag(v1);  % V1 is the primary 'X' dimension vector

    v2 = m_y - m_common;
    v2 = v2 / VMag(v2);

    v3 = cross(v1, v2);  % V3 is the primary 'Z' dimension vector
    v3 = v3 / VMag(v3);

    v2 = cross(v3, v1);  % V2 is the primary 'Y' dimension vector
end

%% Vmag
% This function is used to evaluate the magnitude of a vector in a 3D space
% it requires a 1x3 or a 3x1 vector as input and gives a scalar value of
% the magnitude of the vector in input
function OutValue = VMag(ThreeVector)

    if length(ThreeVector) ~= 3
        error('Input vector must be a 3-vector')
    else
        OutValue = sqrt(sum(ThreeVector.^2));
    end
end
IV. BOW KINEMATICS CALCULATOR PER TRIAL

%% Sarah Hayden
% February 9th, 2024
% Attack_Residual_NEW: This section loads data from two files, extracts
% relevant columns, computes baseline angles per string, and then computes
% residuals for each trial, representing the deviation of attack angles
% from baseline. The results are stored in output tables and saved to .mat
% files.
% Skew_NEW: Similar to the first section, this part loads data, computes
% trial variability (skew) based on average yaw angles, and stores the
% results in an output table saved to a .mat file.
% MeanSmooth_NEW: This section calculates trial variability (mean
% choppiness) based on smooth angle data and saves the results to a .mat
% file.
% Output file has 100 rows (one per subject), 50 columns for 50 trial data

clc
clear all
close all

%% Attack_Residual_NEW
% Load the data
load('OutputTable20240124T1515.mat')
load('Sarah_Hayden_NewAngles.mat')

% Extract relevant columns from inputData
relevantData = MT(:, {'SubID', 'TrialNum', 'Condition', 'PitchAttackAngles', 'PlayedString'});
revData = AttackAngleDataTable(:, {'SubID', 'Condition', 'TrialNum', 'OnsetNum', 'avgAttackAngles', 'avgYawAngle', 'stdYawAngle', 'smoothAngle'});

% Find unique subjects
subjects = unique(relevantData.SubID);

% Initialize trial variability array
trialVariability = zeros(length(subjects), 50);
% Initialize trial variability table
trialVariabilityTable = table('Size', [length(subjects), 52], 'VariableTypes', {'string', 'string', repmat({'double'}, 1, 50)}, ...

% Initialize output table
baselineangles = table('Size', [length(subjects), 6], 'VariableTypes', {'string', 'string', 'double', 'double', 'double', 'double'}, ...
  'VariableNames', {'SubId', 'Condition', 'meanAngle1', 'meanAngle2', 'meanAngle3', 'meanAngle4'});
subjectID_column = cell(length(subjects), 1); % Initialize as 100x1 cell array
color_column = cell(length(subjects), 1); % Initialize as 100x1 cell array

% Assuming subjects is a cell array of subject IDs
for s = 1:length(subjects)
    subjectID = subjects{s};
    % Assuming relevantData is a table containing subject data
    subjectData = relevantData(relevantData.SubID == subjectID, :);
    condition = subjectData.Condition(1); % Assuming you want the first condition
    % Store subject ID and condition in respective columns
    subjectID_column{s} = subjectID;
    condition_column{s} = condition;
end

% Iterate through each subject
for s = 1:length(subjects)
    subjectID = subjects{s};

    % Extract data for this subject
    subjectData = relevantData(relevantData.SubID == subjectID, :);
    subjectData_NEW = revData(string(revData.SubID) == subjectID, :);
    condition = subjectData.Condition(1);

    % Find unique trials for this subject
    trials = unique(subjectData.TrialNum);

    % Initialize arrays to store baseline angles per string
    baselineString1Data = [];
    baselineString2Data = [];
    baselineString3Data = [];
    baselineString4Data = [];

    % Iterate through each trial for this subject to accumulate baseline data
    for t = 1:length(trials)
        trialNum = trials(t);
        % Check if the trial is within 8-10
        if t >= 8 && t <= 10
            % Extract relevant data for this trial
            trialData = subjectData(subjectData.TrialNum == trialNum,:);
            angles = trialData.PitchAttackAngles; % Extracting angles
            stringPlayed = trialData.PlayedString; % Extracting controlString

            % Iterate through each note onset
            for n = 1:length(stringPlayed)
                % Extract string index from control string
                if ismissing(stringPlayed(n))
                    stringIdx = NaN;
                elseif contains(stringPlayed(n), '+')
                    % Split the string by '+' symbol
                    splitStr = strsplit(stringPlayed(n), '+');
                    % Extract the first number
                    numValue = str2double(splitStr{1});
                    if isnan(numValue)
                        % Assign NaN to stringIdx if the first part is not a number
                        stringIdx = NaN;
                    else
                        stringIdx = numValue;
                    end
            end
        end
    end
end
stringIdx = NaN;
else
    % Assign the numeric value to stringIdx
    stringIdx = numValue;
end
else
    % Attempt to convert controlString to a number
    str2double(stringPlayed(n));
    numValue = str2double(stringPlayed(n));
    if isnan(numValue)
        % Assign NaN to stringIdx if controlString is not a number
        stringIdx = NaN;
    else
        % Assign the numeric value to stringIdx
        stringIdx = numValue;
    end
end

% Store the angle in the corresponding string's array
if ~isnan(stringIdx) && ismember(stringIdx, [1, 2, 3, 4])
    switch stringIdx
    case 1
        baselineString1Data = [baselineString1Data,
        angles(n)];
        case 2
        baselineString2Data = [baselineString2Data,
        angles(n)];
        case 3
        baselineString3Data = [baselineString3Data,
        angles(n)];
        case 4
        baselineString4Data = [baselineString4Data,
        angles(n)];
    end
end

% Compute mean baseline angle per string for this subject
meanAngle1 = nanmean(baselineString1Data);
meanAngle2 = nanmean(baselineString2Data);
meanAngle3 = nanmean(baselineString3Data);
meanAngle4 = nanmean(baselineString4Data);

% Store the results in the output table
baselineangles(s, :) = {subjectID, condition, meanAngle1, meanAngle2,
meanAngle3, meanAngle4};

% Iterate through each trial for this subject again to compute residuals
for t = 1:length(trials)
    trialNum = trials(t);
    % Extract relevant data for this trial
    trialData = subjectData(subjectData.TrialNum == trialNum,:);
    angles = trialData.PitchAttackAngles; % Extracting angles
    stringPlayed = trialData.PlayedString; % Extracting controlString

    % Initialize arrays to store attack angles per string
    stringAngles1 = [];
    stringAngles2 = [];

stringAngles3 = [];
stringAngles4 = [];

% Iterate through each note onset
for n = 1:length(stringPlayed)
    % Extract string index from control string
    if ismissing(stringPlayed(n))
        stringIdx = NaN;
    elseif contains(stringPlayed(n), '+')
        % Split the string by '+' symbol
        splitStr = strsplit(stringPlayed(n), '+');
        % Extract the first number
        numValue = str2double(splitStr{1});
        if isnan(numValue)
            % Assign NaN to stringIdx if the first part is not a number
            stringIdx = NaN;
        else
            % Assign the numeric value to stringIdx
            stringIdx = numValue;
        end
    else
        % Attempt to convert controlString to a number
        numValue = str2double(stringPlayed{n});
        if isnan(numValue)
            % Assign NaN to stringIdx if controlString is not a number
            stringIdx = NaN;
        else
            % Assign the numeric value to stringIdx
            stringIdx = numValue;
        end
    end

    % Store the angle in the corresponding string's array
    if ~isnan(stringIdx) && ismember(stringIdx, [1, 2, 3, 4])
        switch stringIdx
            case 1
                stringAngles1 = [stringAngles1, angles(n)];
            case 2
                stringAngles2 = [stringAngles2, angles(n)];
            case 3
                stringAngles3 = [stringAngles3, angles(n)];
            case 4
                stringAngles4 = [stringAngles4, angles(n)];
        end
    end
end

allStringAngles = [stringAngles1(:); stringAngles2(:);
stringAngles3(:); stringAngles4(:)];
allMeanAngles = [repmat(meanAngle1, size(stringAngles1(:)));
    ...
    repmat(meanAngle2, size(stringAngles2(:)));
    ...]
residuals = allStringAngles - allMeanAngles;

% Compute residuals for this trial
residuals = zeros(size(allStringAngles));
for r = 1:length(allStringAngles)
    if ismissing(stringPlayed(r))
        % Assign NaN to stringIdx if controlString contains <missing>
        stringIdx = NaN;
    end
end
% elseif contains(stringPlayed(r), '+')
%     % Split the string by '+' symbol
%     splitStr = strsplit(stringPlayed{r}, '+');
%     % Extract the first number
%     numValue2 = str2double(splitStr{1});
%     if isnan(numValue2)
%         % Assign NaN to stringIdx if the first part is not a number
%         stringIdx = NaN;
%     else
%         % Assign the numeric value to stringIdx
%         stringIdx = numValue2;
%     end
% else
%     % Attempt to convert controlString to a number
%     numValue2 = str2double(stringPlayed{r});
%     if isnan(numValue2)
%         % Assign NaN to stringIdx if controlString is not a number
%         stringIdx = NaN;
%     else
%         % Assign the numeric value to stringIdx
%         stringIdx = numValue2;
%     end
% end
% switch stringIdx
%     case 1
%         residuals(r) = angles(r) - meanAngle1;
%     case 2
%         residuals(r) = angles(r) - meanAngle2;
%     case 3
%         residuals(r) = angles(r) - meanAngle3;
%     case 4
%         residuals(r) = angles(r) - meanAngle4;
% end
% end
% switch stringIdx
%     case 1
%         residuals(r) = allStringAngles(r) - meanAngle1;
%     case 2
%         residuals(r) = allStringAngles(r) - meanAngle2;
%     case 3
%         residuals(r) = allStringAngles(r) - meanAngle3;
%     case 4
%         residuals(r) = allStringAngles(r) - meanAngle4;
% end
% end
% Compute variability for this trial and store it in the appropriate place
trialVariability(s, t) = nanstd(residuals);
end

% Print completion message
fprintf('Subject %s attack analysis completed.\n', subjectID);
end

% Store the results in the output table
trialVariabilityTable = [subjectID_column, condition_column, 
num2cell(trialVariability)];

% Save the resulting table as a .mat file
save('Attack_baselineangles_NEW.mat', 'baselineangles');

% Save trial variability data to a separate file if needed
save('Attack_Residual_NEW.mat', 'trialVariabilityTable');

%% Skew_NEW
clc
clear all
close all
load('Sarah_Hayden_NewAngles.mat')
revData = AttackAngleDataTable(:, {
'SubID', 'Condition', 'TrialNum', 'OnsetNum', 'avgAttackAngles', 'avgYawAngle', 'stdYawAngle', 'smoothAngle'});

% Find unique subjects
subjects = unique(string(revData.SubID));

% Initialize trial variability array
trialVariability = zeros(length(subjects), 50); % Initialize trial variability table
trialVariabilityTable = table('Size', [length(subjects), 52], 'VariableTypes', 
[string, string], repmat({"double"}, 1, 50)], ... % VariableNames', 
}...)

subjectID_column = cell(length(subjects), 1); % Initialize as 100x1 cell array
condition_column = cell(length(subjects), 1); % Initialize as 100x1 cell array

% Assuming subjects is a cell array of subject IDs
for s = 1:length(subjects)
    subjectID = subjects{s};
    % Assuming relevantData is a table containing subject data
    subjectData_NEW = revData(string(revData.SubID) == subjectID, :);
    condition = subjectData_NEW.Condition(1); % Assuming you want the first condition
    % Store subject ID and condition in respective columns
    subjectID_column{s} = subjectID;
    condition_column{s} = condition;
end

% Iterate through each subject
for s = 1:length(subjects)
    subjectID = subjects{s};
    % Extract data for this subject
    subjectData_NEW = revData(string(revData.SubID) == subjectID, :);
condition = subjectData_NEW.Condition(1);  % Assuming you want the first condition

% Find unique trials for this subject
trials = unique(subjectData_NEW.TrialNum);

% Iterate through each trial for this subject again to compute residuals
for t = 1:length(trials)
    trialNum = trials(t);

    % Extract relevant data for this trial
    trialData = subjectData_NEW(subjectData_NEW.TrialNum == trialNum,:);
    angles = trialData.avgYawAngle;  % Extracting angles

    total_yaw = [];  % Initialize array to store avgYawAngle values

    % Iterate through each note onset
    for n = 1:length(trialData.OnsetNum)
        onsetData = trialData(trialData.OnsetNum == n,:);
        total_yaw = [total_yaw, onsetData.avgYawAngle];  % Accumulate avgYawAngle values
    end

    % Compute variability for this trial and store it in the appropriate place
    trialVariability(s, t) = nanstd(total_yaw);  % Use nanstd to handle NaNs
end

% Print completion message
fprintf('Subject %s skew analysis completed.\n', subjectID);
end

% Store the results in the output table
trialVariabilityTable = [subjectID_column, condition_column, num2cell(trialVariability)];

% Save trial variability data to a separate file if needed
save('Skew_NEW.mat', 'trialVariabilityTable');

%% MeanSmooth_NEW
clc
clear all
close all

load('Sarah_Hayden_NewAngles.mat')

revData = AttackAngleDataTable(:, {'SubID', 'Condition', 'TrialNum', 'OnsetNum', 'avgAttackAngles', 'avgYawAngle', 'stdYawAngle', 'smoothAngle'});

% Find unique subjects
subjects = unique(string(revData.SubID));

% Initialize trial variability array
trialVariability = zeros(length(subjects), 50);

% Initialize trial variability table
trialVariabilityTable = table('Size', [length(subjects), 52], 'VariableTypes', ['string', 'string'], 'repmat({"double"}, 1, 50), ... 'VariableNames', {
subjectID_column = cell(length(subjects), 1); % Initialize as 100x1 cell array
column_column = cell(length(subjects), 1); % Initialize as 100x1 cell array

% Assuming subjects is a cell array of subject IDs
for s = 1:length(subjects)
    subjectID = subjects{s};
    subjectData_NEW = revData(string(revData.SubID) == subjectID, :);
    condition = subjectData_NEW.Condition(1); % Assuming you want the first
    % Store subject ID and condition in respective columns
    subjectID_column{s} = subjectID;
    condition_column{s} = condition;
end

% Iterate through each subject
for s = 1:length(subjects)
    subjectID = subjects{s};
    subjectData_NEW = revData(string(revData.SubID) == subjectID, :);
    condition = subjectData_NEW.Condition(1); % Assuming you want the first
    % Find unique trials for this subject
    trials = unique(subjectData_NEW.TrialNum);
    % Iterate through each trial for this subject again to compute residuals
    for t = 1:length(trials)
        trialNum = trials(t);
        % Extract relevant data for this trial
        trialData = subjectData_NEW(subjectData_NEW.TrialNum == trialNum,:);
        angles = trialData.smoothAngle; % Extracting angles
        total_smooth = []; % Initialize array to store avgYawAngle values
        % Iterate through each note onset
        for n = 1:length(trialData.OnsetNum)
            onsetData = trialData(trialData.OnsetNum == n,:);
            total_smooth = [total_smooth, onsetData.smoothAngle]; % Accumulate
        end
        % Compute variability for this trial and store it in the appropriate
        trialVariability(s, t) = nanmean(total_smooth); % Use nanstd to handle NaNs
    end
end
% Print completion message
fprintf('Subject %s smooth analysis completed.\n', subjectID);
end

% Store the results in the output table
trialVariabilityTable = [subjectID_column, condition_column, num2cell(trialVariability)];

% Save trial variability data to a separate file if needed
save('MeanSmooth_NEW.mat', 'trialVariabilityTable');

%% Devon Lantagne's Function
% ComputeAttackAngles
function [PitchAngles, YawAngles] = ComputeAttackAngles(obj, frames)
% Returns two Fx1 array of pitch and yaw angles between the bow and strings.
% First col are pitch angles and second col are yaw angles.
% frames is an optional input argument. Used to specify
% specific frames to shorten computation. If left blank,
% will use all frames.
% Assume the violinist is right-handed:
% - pitch angles are negative when hitting G string; positive for E string, and zero for the bow parallel to the plane of the violin.
% - yaw angles are zero when the bow is hitting the strings perpendicularly, positive if the bow tip is pointing toward the scroll, negative if pointing toward the violinist.
% Violin normal vector is computed as the cross product between two vectors with a common point (defined by ViolinNormRefMarks).
% Violin axial vector represents the strings and is used for yaw angles.
% Bow vector is the line between the extremes of the bow (markers 7 (tip) and 10 (windings)).
% if nargin < 2
% frames = 1:obj.MarkerFrames;
% end
%
% Preallocate output array
PitchAngles = NaN(length(frames), 1);
if nargout > 1
YawAngles = NaN(length(frames), 1);
end

% For every frame
for OutIdx = 1:length(frames)
frame = frames(OutIdx);
% Collect points of interest. If any are NaN, return NaN angles.
% Bow Line Points
BP_W = obj.Markers.Bow{frame, 'M10'}; % Handle (winding)
BP_T = obj.Markers.Bow{frame, 'M7'}; % Tip
% Bow unit vector
BowVector = BP_T - BP_W;
if any(isnan(BowVector))
    % If we don't have a bow line, we can't compute anything
    continue
end
BowVector = BowVector / norm(BowVector);

% Compute Pitch Angle

% Violin Plane Points

% Find unit vector normal to violin plane
[~, ~, VP_N] = GetBasisVector(VP_Common, VP_Axial, VP_Perp);

% Pitch Angle
PitchAngles(OutIdx) = 90 - acosd( dot(BowVector, VP_N));

% Yaw Angle
if (nargout > 1) && obj.HasMarker('MS')

    % Get Strings Points
    VP_Tail = obj.Markers.Violin{frame, 'M5'};
    VP_Scroll = obj.Markers.Violin{frame, 'MS'};

    % Get strings unit vector
    StringVector = VP_Scroll - VP_Tail;
    StringVector = StringVector / norm(StringVector); % Normalize

    YawAngles(OutIdx) = 90 - acosd( dot(BowVector, StringVector));
end
end

function [freq, frame_total] = open_ndi_bin_file(ndiFileName)
% function [ndi_array, freq, frame_total] = open_ndi_bin_file(ndiFileName)
% Try to open the file
fid = fopen(ndiFileName, 'r');
if fid == -1
    error('Failed to open the file: %s', ndiFileName);
end

try
    % Read file contents
    fread(fid, 1, 'char'); % 32
    item_total = fread(fid, 1, 'short'); % items per frame
    subitem_total = fread(fid, 1, 'short'); % subitems per frame
    column_total = item_total * subitem_total;
    frame_total = fread(fid, 1, 'int'); % number of frames
    freq = fread(fid, 1, 'float'); % collection frame frequency
    fread(fid, 60, 'char=>char'); % user comments
    fread(fid, 60, 'char=>char'); % system comments
    fread(fid, 30, 'char=>char'); % file description
end
fread(fid, 1, 'short');             % cutoff filter frequency
fread(fid, 8, 'char=>char');       % time of collection
fread(fid, 1, 'short');            % unused?
fread(fid, 8, 'char=>char');       % date of collection
fread(fid, 73, 'char');            % extended header and

unused

ndi_array = ones(frame_total, column_total) .* NaN;

for frame_num = 1:frame_total
    for column_num = 1:column_total
        data = fread(fid, 1, 'float');  
        if (data < -100000) % technically, it is EE EE EE EE or -
            data = NaN;               
        end
        ndi_array(frame_num, column_num) = data;
    end
end

catch ME
    % Close the file if an error occurs
    fclose(fid);
    rethrow(ME);
end

% Close the file
fclose(fid);

%% GetBasisVector
% Starting from three different points, this function create an orthonormal
% triade of vectors. m_common, m_x and m_y must be three dimensional
% points in the space

function [v1, v2, v3] = GetBasisVector (m_common, m_x, m_y)
    v1 = m_x - m_common;
    v1 = v1 / VMag(v1);    % V1 is the primary 'X' dimension vector

    v2 = m_y - m_common;
    v2 = v2 / VMag(v2);

    v3 = cross(v1, v2);   % V3 is the primary 'Z' dimension vector
    v3 = v3 / VMag(v3);

    v2 = cross(v3, v1);   % V2 is the primary 'Y' dimension vector
end

%% Vmag
% This function is used to evaluate the magnitude of a vector in a 3D space
% it requires a 1x3 or a 3x1 vector as input and gives a scalar value of
% the magnitude of the vector in input

function OutValue = VMag(ThreeVector)
    if length(ThreeVector) ~= 3
        error('Input vector must be a 3-vector')
    else
        OutValue = sqrt(sum(ThreeVector.^2));
    end
V. PLOTTING BOW KINEMATIC PERFORMANCE MEASURES

%% Sarah Hayden
% February 10th, 2024
%
% This code reads in the 100x50 tables per dependent variable. It then
% calculates the standard error for each dependent variable based on the
% trial variability data. The standard error is a measure of the
% variability of the sample means around the population mean.
%
% After computing the standard error, the script generates a plot showing
% the standard error of mean trial variability per dependent variable. This
% plot provides insight into the variability of the data across different
% conditions or subjects.
%
% Additionally, the script outputs EPOC (Experimental Paradigm for Open
% Calls) data tables per dependent variable. These tables are written to
% separate CSV files, with each file containing the trial variability data
% for a specific dependent variable.

clear all
close all
clc

load Attack_Residual_NEW.mat
attack_angles = trialVariabilityTable;
clear trialVariabilityTable;

load skew_new.mat
skew_angles = trialVariabilityTable;
clear trialVariabilityTable;

load MeanSmooth_NEW.mat
meansmooth_angles = trialVariabilityTable;

Subj_all = trialVariabilityTable(:,1);
Subj_cell = char(Subj_all);

% Extract the last character from each string in Subj_cell
GroupCodes = Subj_cell(:,end);

% Convert the cell array of characters to a character array
GroupCodesCell = char(GroupCodes);

% Filter data based on conditions
Subj_C = find(GroupCodesCell == 'C');
Subj_I = find(GroupCodesCell == 'I');
Subj_S = find(GroupCodesCell == 'S');

num_subj = length(Subj_all);

attack = attack_angles(:,3:52);
skew = skew_angles(:,3:52);
meansmooth = meansmooth_angles(:,3:52);

CONTROLS = find(GroupCodesCell == 'C');
INVERTEDS = find(GroupCodesCell == 'I');
SHUFFLEDS = find(GroupCodesCell == 'S');
%% attack
figure
% Convert cell arrays to numeric arrays
attack_numeric_controls = cell2mat(attack(CONTROLS,:));
attack_numeric_inverteds = cell2mat(attack(INVERTEDS,:));
attack_numeric_shuffleds = cell2mat(attack(SHUFFLEDS,:));
plot(nanmean(attack_numeric_controls),'b') %using nanmean because I build the
hold on
y1=nanmean(attack_numeric_controls)+nanstd(attack_numeric_controls)/sqrt(length
(CONTROLS));
y2=nanmean(attack_numeric_controls)-
nanstd(attack_numeric_controls)/sqrt(length(CONTROLS));
x = [1:50, fliplr(1:50)];
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'b');
plot(nanmean(attack_numeric_inverteds),'r')
y1=nanmean(attack_numeric_inverteds)+nanstd(attack_numeric_inverteds)/sqrt(leng
th(INVERTEDS));
y2=nanmean(attack_numeric_inverteds)-
nanstd(attack_numeric_inverteds)/sqrt(length(INVERTEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'r');
plot(nanmean(attack_numeric_shuffleds),'g')
y1=nanmean(attack_numeric_shuffleds)+nanstd(attack_numeric_shuffleds)/sqrt(leng
th(SHUFFLEDS));
y2=nanmean(attack_numeric_shuffleds)-
nanstd(attack_numeric_shuffleds)/sqrt(length(SHUFFLEDS));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'g');

indx=36;
plot(indx*ones(size(CONTROLS)),attack_numeric_controls(:,indx),'b.','MarkerSize
',4);
V = axis;
xline(10,V)
xline(40,V)
ylabel('Attack Angles Residual Stdev')
xlabel('Trial')
legend('Control','','Inverted','','Shuffled','')
title('Stdev Attack Angle Residual')

%% skew
figure
% Convert cell arrays to numeric arrays
skew_numeric_controls = cell2mat(skew(CONTROLS,:));
skew_numeric_inverteds = cell2mat(skew(INVERTEDS,:));
skew_numeric_shuffleds = cell2mat(skew(SHUFFLEDS,:));
plot(nanmean(skew_numeric_controls),'b')
hold on
y1=nanmean(skew_numeric_controls)+nanstd(skew_numeric_controls)/sqrt(length(CON
TROLS));
y2=nanmean(skew_numeric_controls)-
nanstd(skew_numeric_controls)/sqrt(length(CONTROLS));
x = [1:50, fliplr(1:50)];
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'b');
plot(nanmean(skew_numeric_inverted), 'r')
y1 = nanmean(skew_numeric_inverted) + nanstd(skew_numeric_inverted)/sqrt(length(INVERTED));
y2 = nanmean(skew_numeric_inverted) - nanstd(skew_numeric_inverted)/sqrt(length(INVERTED));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'r');
plot(nanmean(skew_numeric_shuffled), 'g')
y1 = nanmean(skew_numeric_shuffled) + nanstd(skew_numeric_shuffled)/sqrt(length(SHUFFLED));
y2 = nanmean(skew_numeric_shuffled) - nanstd(skew_numeric_shuffled)/sqrt(length(SHUFFLED));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'g');

V = axis;
xline(10, V)
xline(40, V)
ylabel('Skew Angles Stdev')
xlabel('Trial')
legend('Control', ' ', 'Inverted', ' ', 'Shuffled', ' ')
title('Stdev Skew Angle per Trial (Averaged Per Note Onset)')

%% meansmooth
figure
% Convert cell arrays to numeric arrays
meansmooth_numeric_controls = cell2mat(meansmooth(CONTROLS,:));
meansmooth_numeric_inverted = cell2mat(meansmooth(INVERTED,:));
meansmooth_numeric_shuffled = cell2mat(meansmooth(SHUFFLED,:));
plot(nanmean(meansmooth_numeric_controls), 'b')
hold on
y1 = nanmean(meansmooth_numeric_controls) + nanstd(meansmooth_numeric_controls)/sqrt(length(CONTROLS));
y2 = nanmean(meansmooth_numeric_controls) - nanstd(meansmooth_numeric_controls)/sqrt(length(CONTROLS));
x = [1:50, fliplr(1:50)];
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'b');
plot(nanmean(meansmooth_numeric_inverted), 'r')
y1 = nanmean(meansmooth_numeric_inverted) + nanstd(meansmooth_numeric_inverted)/sqrt(length(INVERTED));
y2 = nanmean(meansmooth_numeric_inverted) - nanstd(meansmooth_numeric_inverted)/sqrt(length(INVERTED));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'r');
plot(nanmean(meansmooth_numeric_shuffled), 'g')
y1 = nanmean(meansmooth_numeric_shuffled) + nanstd(meansmooth_numeric_shuffled)/sqrt(length(SHUFFLED));
y2 = nanmean(meansmooth_numeric_shuffled) - nanstd(meansmooth_numeric_shuffled)/sqrt(length(SHUFFLED));
inBetween = [y1, fliplr(y2)];
fill(x, inBetween, 'g');
V = axis;
xline(10,V)
xline(40,V)
ylabel('Smooth Angles (deg)')
xlabel('Trial')
legend('Control','Inverted','Shuffled')
title('Mean Smooth Angle per Trial (Stdev Per Note Onset)')

%% EPOCS
GroupCodes = cellstr(GroupCodes);

% Define trial blocks
trial_blocks = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test',
'Initial Washout', 'Final Washout'};
variable_xaxis = {'Attack', 'Skew', 'MeanSmooth'};

% Define indices for grouping and variable arrays
groups = {8:10, 11:13, 24:26, 38:40, 41:43, 48:50};
variable_arrays = {attack, skew, stdskew, smooth, meansmooth, skewvar,
smooth_velvar, AAVel}; % Assuming attack, skew, smooth are defined elsewhere
variable_names = {'attack', 'skew', 'meansmooth', };%

% Initialize cell array to store new variable arrays
new_variable_arrays = cell(1, length(variable_arrays));

% Iterate over variable arrays
for var_idx = 1:length(variable_arrays)
    % Initialize cell array to store average values for each trial block
    new_variable_array = cell(size(variable_arrays{var_idx}, 1),
    length(groups));

    % Iterate over groups
    for group_idx = 1:length(groups)
        % Extract data for the current group
        data = variable_arrays{var_idx}(:, groups{group_idx});

        % Take the average of the columns and store in the new variable array
        new_variable_array(:, group_idx) = num2cell(nanmean(cell2mat(data),
        2));
    end

    % Store the new variable array with a dynamically generated name
    new_var_name = [variable_names{var_idx} '_block'];
    new_variable_arrays{var_idx} = new_variable_array;

    % Assign the new variable array to the workspace
    assignin('base', new_var_name, new_variable_array);
end

% Concatenate 'Subj_all' to each variable array
attack_block = [Subj_all, GroupCodes, attack_block];
skew_block = [Subj_all, GroupCodes, skew_block];
meansmooth_block = [Subj_all, GroupCodes, meansmooth_block];

% Save the new variable arrays into separate .mat files
save('attack_block.mat', 'attack_block');
save('skew_block.mat', 'skew_block');
save('meansmooth_block.mat', 'meansmooth_block');

load('attack_block.mat')
load('skew_block.mat')
load('meansmooth_block.mat')

Subj_all = attack_block(:,1);
Subj_cell = char(Subj_all);

% Extract the last character from each string in Subj_cell
GroupCodes = Subj_cell(:,end);

% Convert the cell array of characters to a character array
GroupCodesCell = char(GroupCodes);

% Filter data based on conditions
Subj_C = find(GroupCodesCell == 'C');
Subj_I = find(GroupCodesCell == 'I');
Subj_S = find(GroupCodesCell == 'S');

x_values = 1:6;
y_values_attack = attack_block(:, 3:8);
y_values_skew = skew_block(:,3:8);
y_values_meansmooth = meansmooth_block(:,3:8);

num_subj = length(Subj_all);

% Define colors for each group
controlColor = 'k';
invertedColor = 'r';
shuffledColor = 'b';

%% AA Residual EPOC
% Create scatter plots for each group
figure;
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;
t = tiledlayout(2,2);
ax1 = nexttile;
scatter(x_values, cell2mat(y_values_attack(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor);
hold on;
data_matrix_C = cell2mat(y_values_attack(Subj_C, :));
boxplot(data_matrix_C, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', controlColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Control');
```
scatter(x_values, cell2mat(y_values_attack(Subj_I, :)), 'Marker', 'x', 'MarkerFaceColor', invertedColor, 'MarkerEdgeColor', invertedColor);
hold on;
data_matrix_I = cell2mat(y_values_attack(Subj_I, :));
boxplot(data_matrix_I, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', invertedColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Inverted');
hold on;

scatter(x_values, cell2mat(y_values_attack(Subj_S, :)), 'Marker', '+', 'MarkerFaceColor', shuffledColor, 'MarkerEdgeColor', shuffledColor);
hold on;
data_matrix_S = cell2mat(y_values_attack(Subj_S, :));
boxplot(data_matrix_S, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', shuffledColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Shuffled');
hold off;

% Create a combined scatter plot
ax4 = nexttile;
offset = 0.25; % Adjust the offset value according to your preference
scatter(x_values - offset, cell2mat(y_values_attack(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor, 'DisplayName', 'Control');
hold on;
scatter(x_values, cell2mat(y_values_attack(Subj_I, :)), 'Marker', 'x', 'MarkerEdgeColor', invertedColor, 'DisplayName', 'Inverted');
scatter(x_values + offset, cell2mat(y_values_attack(Subj_S, :)), 'Marker', '+', 'MarkerFaceColor', shuffledColor, 'DisplayName', 'Shuffled');
hold off;
title('Combined Plot');
hold on;

% Adjust layout
title(t, 'Residual Attack Angle Trial Blocking Average')
xlabel(t, 'Trial Numbers Averaged Together')
```
ylabel(t,'Attack Angles Residual Stdev')
linkaxes([ax1 ax2 ax3 ax4], 'xy');

%% Stdev Skew Angle per Trial (Averaged Per Note Onset)
% Create scatter plots for each group
figure;
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;

t = tiledlayout(2,2);
ax1 = nexttile;
scatter(x_values, cell2mat(y_values_skew(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor);
hold on;
data_matrix_C = cell2mat(y_values_skew(Subj_C, :));
boxplot(data_matrix_C, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', controlColor);
set(findobj(gca,'Tag', 'Median'), 'Color', 'k');
title('Control');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xlim([0 6])
% ylim([12 18])
% yline(.43, 'k--', 'LineWidth', 2);
hold off;

ax2 = nexttile;
scatter(x_values, cell2mat(y_values_skew(Subj_I, :)), 'Marker', 'x', 'MarkerFaceColor', invertedColor, 'MarkerEdgeColor', invertedColor);
hold on;
data_matrix_I = cell2mat(y_values_skew(Subj_I, :));
boxplot(data_matrix_I, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', invertedColor);
set(findobj(gca,'Tag', 'Median'), 'Color', 'k');
title('Inverted');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xlim([0 6])
% ylim([12 18])
% yline(.43, 'k--', 'LineWidth', 2);
hold off;

ax3 = nexttile;
scatter(x_values, cell2mat(y_values_skew(Subj_S, :)), 'Marker', '+', 'MarkerFaceColor', shuffledColor, 'MarkerEdgeColor', shuffledColor);
hold on;
data_matrix_S = cell2mat(y_values_skew(Subj_S, :));
boxplot(data_matrix_S, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', shuffledColor);
set(findobj(gca,'Tag', 'Median'), 'Color', 'k');
title('Shuffled');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xlim([0 6])
% ylim([12 18])
% yline(.43, 'k--', 'LineWidth', 2);
hold off;
% Create a combined scatter plot
ax4 = nexttile;
offset = 0.25; % Adjust the offset value according to your preference
scatter(x_values - offset, cell2mat(y_values_skew(Subj_C, :)), 'Marker', 'o',
'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor,
'DisplayName', 'Control');
hold on;
scatter(x_values, cell2mat(y_values_skew(Subj_I, :)), 'Marker', 'x',
'MarkerFaceColor', invertedColor, 'DisplayName', 'Inverted');
scatter(x_values + offset, cell2mat(y_values_skew(Subj_S, :)), 'Marker', '+',
'MarkerFaceColor', shuffledColor, 'DisplayName', 'Shuffled');
hold off;

title('Combined Plot');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% ylim([12 18])
% yline(.43, 'k--', 'LineWidth', 2);

% Adjust layout
title(t, 'Stdev Skew Angle per Trial (Averaged Per Note Onset)')
%xlabel(t,'Trial Numbers Averaged Together')
ylabel(t, 'Skew Angle Stdev')
linkaxes([ax1 ax2 ax3 ax4], 'xy');

% Create scatter plots for each group
figure;
xlabels = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;
t = tiledlayout(2,2);
ax1 = nexttile;
scatter(x_values, cell2mat(y_values_stdskew(Subj_C, :)), 'Marker', 'o',
'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor);
hold on;
data_matrix_C = cell2mat(y_values_stdskew(Subj_C, :));
boxplot(data_matrix_C, 'Positions', x_values + offset, 'Widths', 0.1,
'BoxStyle', 'filled', 'Colors', controlColor);
set(findobj(gca,'Tag','Median'),'Color','k');
title('Control');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% ylim([12 18])
% yline(.43, 'k--', 'LineWidth', 2);
hold off;
ax2 = nexttile;
scatter(x_values, cell2mat(y_values_stdskew(Subj_I, :)), 'Marker', 'x', 'MarkerFaceColor', invertedColor, 'MarkerEdgeColor', invertedColor);
hold on;
data_matrix_I = cell2mat(y_values_stdskew(Subj_I, :));
boxplot(data_matrix_I, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', invertedColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Inverted');

% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% yline(.43, 'k--', 'LineWidth', 2);
hold off;

ax3 = nexttile;
scatter(x_values, cell2mat(y_values_stdskew(Subj_S, :)), 'Marker', '+', 'MarkerFaceColor', shuffledColor, 'MarkerEdgeColor', shuffledColor);
hold on;
data_matrix_S = cell2mat(y_values_stdskew(Subj_S, :));
boxplot(data_matrix_S, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', shuffledColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Shuffled');

% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% yline(.43, 'k--', 'LineWidth', 2);
hold off;

% Create a combined scatter plot
ax4 = nexttile;
offset = 0.25; % Adjust the offset value according to your preference
scatter(x_values - offset, cell2mat(y_values_stdskew(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor, 'DisplayName', 'Control');
hold on;
scatter(x_values, cell2mat(y_values_stdskew(Subj_I, :)), 'Marker', 'x', 'MarkerEdgeColor', invertedColor, 'DisplayName', 'Inverted');
scatter(x_values + offset, cell2mat(y_values_stdskew(Subj_S, :)), 'Marker', '+', 'MarkerEdgeColor', shuffledColor, 'DisplayName', 'Shuffled');
hold off;

title('Combined Plot');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% yline(.43, 'k--', 'LineWidth', 2);
hold off;

% Adjust layout
title(t, 'Stdev Skew Angle per Trial (Stdev Per Note Onset)')
%xlabel(t,'Trial Numbers Averaged Together')
ylabel(t,'Skew Angle Stdev')
linkaxes([ax1 ax2 ax3 ax4],'xy');

%% Mean Smooth Angle per Trial (Stdev Per Note Onset) Blocking
% Create scatter plots for each group
figure;
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;

% Create scatter plots for each group
figure;
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;

% Create scatter plots for each group
figure;
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;

% Create scatter plots for each group
figure;
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;
hold off;

% Create a combined scatter plot
ax4 = nexttile;
offset = 0.25; % Adjust the offset value according to your preference
scatter(x_values - offset, cell2mat(y_values_meansmooth(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor, 'DisplayName', 'Control');
hold on;
scatter(x_values, cell2mat(y_values_meansmooth(Subj_I, :)), 'Marker', 'x', 'MarkerEdgeColor', invertedColor, 'DisplayName', 'Inverted');
scatter(x_values + offset, cell2mat(y_values_meansmooth(Subj_S, :)), 'Marker', '+', 'MarkerEdgeColor', shuffledColor, 'DisplayName', 'Shuffled');
hold off;

title('Combined Plot');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% ylim([12 18])
% yline(13, 'k--', 'LineWidth', 2);

% Adjust layout

% Create scatter plots for each group
figure;
xylbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;
t = tiledlayout(2,2);
ax1 = nexttile;
scatter(x_values, cell2mat(y_values_smooth(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor);
hold on;
data_matrix_C = cell2mat(y_values_smooth(Subj_C, :));
boxplot(data_matrix_C, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', controlColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Control');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% ylim([12 18])
% yline(13, 'k--', 'LineWidth', 2);
hold off;
ax2 = nexttile;
scatter(x_values, cell2mat(y_values_smooth(Subj_I, :)), 'Marker', 'x', 'MarkerFaceColor', invertedColor, 'MarkerEdgeColor', invertedColor);
hold on;
data_matrix_I = cell2mat(y_values_smooth(Subj_I, :));
boxplot(data_matrix_I, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', invertedColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Inverted');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
% define tick locations explicitly
% define tick labels
% ylim([0 6])
% yline(13, 'k--', 'LineWidth', 2);
hold off;

ax3 = nexttile;
scatter(x_values, cell2mat(y_values_smooth(Subj_S, :)), 'Marker', '+', 'MarkerFaceColor', shuffledColor, 'MarkerEdgeColor', shuffledColor);
hold on;
data_matrix_S = cell2mat(y_values_smooth(Subj_S, :));
boxplot(data_matrix_S, 'Positions', x_values + offset, 'Widths', 0.1, 'BoxStyle', 'filled', 'Colors', shuffledColor);
set(findobj(gca, 'Tag', 'Median'), 'Color', 'k');
title('Shuffled');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
% define tick locations explicitly
% define tick labels
% ylim([0 6])
% yline(13, 'k--', 'LineWidth', 2);
hold off;

% Create a combined scatter plot
ax4 = nexttile;
offset = 0.25; % Adjust the offset value according to your preference
scatter(x_values - offset, cell2mat(y_values_smooth(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor, 'DisplayName', 'Control');
hold on;
scatter(x_values, cell2mat(y_values_smooth(Subj_I, :)), 'Marker', 'x', 'MarkerEdgeColor', invertedColor, 'DisplayName', 'Inverted');
scatter(x_values + offset, cell2mat(y_values_smooth(Subj_S, :)), 'Marker', '+', 'MarkerEdgeColor', shuffledColor, 'DisplayName', 'Shuffled');
hold off;
title('Combined Plot');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
% define tick locations explicitly
% define tick labels
% xlim([0 6])
% yline(13, 'k--', 'LineWidth', 2);

% Adjust layout
title(t,'Stdev Smooth Angle per Trial (Stdev Per Note Onset) Blocking')
%xlabel(t,'Trial Numbers Averaged Together')
ylabel(t,'Smooth Angle Stdev')
linkaxes([ax1 ax2 ax3 ax4],'xy');

% Create scatter plots for each group
figure;
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test', 'Initial Washout', 'Final Washout'};
offset = 0.25;

t = tiledlayout(2,2);
ax1 = nexttile;
scatter(x_values, cell2mat(y_values_AAVel_block(Subj_C, :)), 'Marker', 'o',
'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor);
hold on;
data_matrix_C = cell2mat(y_values_AAVel_block(Subj_C, :));
boxplot(data_matrix_C, 'Positions', x_values + offset, 'Widths', 0.1,
'BoxStyle', 'filled', 'Colors', controlColor);
set(findobj(gca,'Tag','Median'),'Color','k');
title('Control');

% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values)
xticklabels(xtlbls)
xlim([0 6])
% ylim([12 18])
% yline(13, 'k--', 'LineWidth', 2);
hold off;

ax2 = nexttile;
scatter(x_values, cell2mat(y_values_AAVel_block(Subj_I, :)), 'Marker', 'x',
'MarkerFaceColor', invertedColor, 'MarkerEdgeColor', invertedColor);
hold on;
data_matrix_I = cell2mat(y_values_AAVel_block(Subj_I, :));
boxplot(data_matrix_I, 'Positions', x_values + offset, 'Widths', 0.1,
'BoxStyle', 'filled', 'Colors', invertedColor);
set(findobj(gca,'Tag','Median'),'Color','k');
title('Inverted');

% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values)
xticklabels(xtlbls)
xlim([0 6])
% ylim([12 18])
% yline(13, 'k--', 'LineWidth', 2);
hold off;

ax3 = nexttile;
scatter(x_values, cell2mat(y_values_AAVel_block(Subj_S, :)), 'Marker', '+',
'MarkerFaceColor', shuffledColor, 'MarkerEdgeColor', shuffledColor);
hold on;
data_matrix_S = cell2mat(y_values_AAVel_block(Subj_S, :));
boxplot(data_matrix_S, 'Positions', x_values + offset, 'Widths', 0.1,
'BoxStyle', 'filled', 'Colors', shuffledColor);
set(findobj(gca,'Tag','Median'),'Color','k');
title('Shuffled');

% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values)
xticklabels(xtlbls)
xlim([0 6])
% yline(13, 'k--', 'LineWidth', 2);
hold off;

% Create a combined scatter plot
ax4 = nexttile;
offset = 0.25; % Adjust the offset value according to your preference
scatter(x_values - offset, cell2mat(y_values_AAVel_block(Subj_C, :)), 'Marker', 'o', 'MarkerFaceColor', controlColor, 'MarkerEdgeColor', controlColor, 'DisplayName', 'Control');
hold on;
scatter(x_values, cell2mat(y_values_AAVel_block(Subj_I, :)), 'Marker', 'x', 'MarkerEdgeColor', invertedColor, 'DisplayName', 'Inverted');
scatter(x_values + offset, cell2mat(y_values_AAVel_block(Subj_S, :)), 'Marker', '+', 'MarkerEdgeColor', shuffledColor, 'DisplayName', 'Shuffled');
hold off;

title('Combined Plot');
% xlabel('X-axis Label');
% ylabel('Y-axis Label');
xticks(x_values) % define tick locations explicitly
xticklabels(xtlbls) % define tick labels
xlim([0 6])
% yline(13, 'k--', 'LineWidth', 2);

% Adjust layout
title(t, 'Attack Velocity Variance Blocking')
% xlabel(t, 'Trial Numbers Averaged Together')
ylabel(t, 'Attack Velocity Variance')
linkaxes([ax1 ax2 ax3 ax4], 'xy');

% function xline (xlocation, V)
hold on
% V = axis;
plot(xlocation*[1 1], V(3:4), 'k--')
return
end

function yline (ylocation)
hold on
V = axis;
plot(V(1:2), ylocation*[1 1], 'k--')
return
end
VI. SKILL GROUPING

%% Sarah Hayden
% February 26th, 2024
% This code runs through every subject, pulls from their listed Suzuki Book
% level number, and organizes them into skill arrays.

clc
clear all
close
dataFolderPath = '/Users/sarahhayden/Library/CloudStorage/OneDrive-
SharedLibraries-MarquetteUniversity/Violinn - Documents/violin project
2022/Devon Code/Data/VSubs/S5 - Note State Machine';
matFiles = dir(fullfile(dataFolderPath, '*.mat'));

% Initialize tables for each group
intermediate_table = table('Size', [0, 3], 'VariableTypes', {'string',
'string', 'double'}, 'VariableNames', {'SubID', 'ConditionName',
'BookNumber'});
advanced_table = table('Size', [0, 3], 'VariableTypes', {'string',
'string', 'double'}, 'VariableNames', {'SubID', 'ConditionName', 'BookNumber'});
extert_table = table('Size', [0, 3], 'VariableTypes', {'string',
'string', 'double'}, 'VariableNames', {'SubID', 'ConditionName', 'BookNumber'});

for fileIdx = 1:length(matFiles)
currentFileName = fullfile(dataFolderPath, matFiles(fileIdx).name);
load(currentFileName, 'VSub');
subID = VSub.SubID;
condition = VSub.ConditionName;
book_number = VSub.SubjectMeta{1, 'BookNumber'};

% Categorize subjects into different groups based on their book number
if any(book_number == [2 3 4 5])
    intermediate_table(end+1, :) = {subID, condition, book_number};
elseif any(book_number == [6 7 8 9])
    advanced_table(end+1, :) = {subID, condition, book_number};
elseif any(book_number == [9.5 10, 11, 0])
    expert_table(end+1, :) = {subID, condition, book_number};
end
end

% Save arrays into the working directory
save('intermediate.mat', 'intermediate_table');
save('advanced.mat', 'advanced_table');
save('expert.mat', 'expert_table');
%% Sarah Hayden
% February 13th, 2024
%
% This code adds on the skill level for each subject in the epoc dependent
% variable .mat files.

%% skill grouping
clear all
close all
clc

% Load skill level .mat files
load('intermediate.mat');  % Assuming it has SubID in variable 'intermediate_table'
load('advanced.mat');      % Assuming it has SubID in variable 'advanced_table'
load('expert.mat');        % Assuming it has SubID in variable 'expert_table'

% Convert tables to cell arrays
intermediate_table = table2cell(intermediate_table);
advanced_table = table2cell(advanced_table);
expert_table = table2cell(expert_table);

% Define skill levels
intermediate_skill = 1;
advanced_skill = 2;
expert_skill = 3;

% Load data files
load('num_notes_new.mat');
load('note_intervvals_new.mat');
load('note_interval_var_new.mat');
load('attack_block.mat')
load('skew_block.mat')
load('meansmooth_block.mat')

% Add skill level column for each data file
datasets = {num_notes_new, note_intervvals_new, note_interval_var_new, 
attack_block, skew_block, meansmooth_block};
modified_datasets = cell(size(datasets)); % Initialize a cell array to store modified datasets
for i = 1:length(datasets)
    data = datasets{i};
    skill_column = zeros(size(data, 1), 1);
    for j = 1:size(data, 1)
        % Get the SubID from the first column
        % Add skill level to each data file
        data(j, 1) = SubID; % Assuming SubID is in the first column
    end
    modified_datasets{i} = [data, skill_column]; % Add skill level column
end

subID = data{j, 1}; % Accessing cell elements using curly braces

% Check the skill level based on the SubID
is_intermediate = false;
is_advanced = false;
is_expert = false;

for k = 1:length(intermediate_table)
    if strcmp(subID, intermediate_table{k})
        is_intermediate = true;
        break;
    end
end

for k = 1:length(advanced_table)
    if strcmp(subID, advanced_table{k})
        is_advanced = true;
        break;
    end
end

for k = 1:length(expert_table)
    if strcmp(subID, expert_table{k})
        is_expert = true;
        break;
    end
end

if is_intermediate
    skill_column(j) = intermediate_skill;
elseif is_advanced
    skill_column(j) = advanced_skill;
elseif is_expert
    skill_column(j) = expert_skill;
else
    % Handle any other cases
    skill_column(j) = NaN; % Or any other value you prefer
end

% Assign the skill level column to the cell array
data_with_skill = [data, num2cell(skill_column)]; % Concatenate skill column
modified_datasets{i} = data_with_skill;
end

% Save the modified .mat files with unique filenames
for i = 1:length(modified_datasets)
data = modified_datasets{i};
filename = sprintf('modified_dataset_%d_with_skill.mat', i);
save(filename, 'data');
end
VIII. PLOT EPOCHS WITH SKILL MARKERS

%% Sarah Hayden
% February 27th, 2024
%
% This code plots the dependent variable EPOC plots with varying marker types per skill.
clc
clear all
close all

% Load the data
data1 = load('modified_dataset_1_with_skill.mat');
data2 = load('modified_dataset_2_with_skill.mat');
data3 = load('modified_dataset_3_with_skill.mat');
data4 = load('modified_dataset_4_with_skill.mat');
data5 = load('modified_dataset_5_with_skill.mat');
data6 = load('modified_dataset_6_with_skill.mat');
data7 = load('modified_dataset_7_with_skill.mat');
data8 = load('modified_dataset_8_with_skill.mat');
data9 = load('modified_dataset_9_with_skill.mat');

% Extract the tables from the structs
num_notes_new = data1.data;
note_intervals_new = data2.data;
note_interval_var_new = data3.data;
% err_trans_new = data4.data;
% ok_trans_new = data5.data;
% note_interval_med_new = data6.data;
attack_block = data7.data;
skew_block = data8.data;
meansmooth_block = data9.data;

Subj_all = num_notes_new(:,1);
Subj_cell = char(Subj_all);
Subj_ids = num_notes_new(:,2);

% Extract the last character from each string in Subj_cell
GroupCodes = Subj_cell(:,end);

% Convert the cell array of characters to a character array
GroupCodesCell = char(GroupCodes);

% Filter data based on conditions
Subj_C = find(GroupCodesCell == 'C');
Subj_I = find(GroupCodesCell == 'I');
Subj_S = find(GroupCodesCell == 'S');

x_values = 1:6;

y_values_NN = num_notes_new(:, 3:8);
y_values_NI = note_intervals_new(:,3:8);
y_values_NIV = note_interval_var_new(:,3:8);
n y_values_ET = err_trans_new(:,3:8);
% y_values_OT = ok_trans_new(:,3:8);
% y_values_MNI = note_interval_med_new(:,3:8);
y_values_AA = attack_block(:,3:8);
y_values_SK = skew_block(:,3:8);
y_values_SM = meansmooth_block(:,3:8);

skill_NN = cell2mat(num_notes_new(:, 9)); % Convert to numeric array
skill_NI = cell2mat(note_intervals_new(:,9));
skill_NIV = cell2mat(note_interval_var_new(:,9));
% skill_ET = cell2mat(err_trans_new(:, 9)); % Convert to numeric array
% skill_OT = cell2mat(ok_trans_new(:,9));
% skill_MNI = cell2mat(note_interval_med_new(:,9));
skill_AA = cell2mat(attack_block(:,9));
skill_SK = cell2mat(skew_block(:,9));
skill_SM = cell2mat(meansmooth_block(:,9));

num_subj = length(Subj_all);

% Define colors for each group
controlColor = 'k';
invertedColor = 'r';
shuffledColor = 'b';

% Define xticklabels
xtlbls = {'Baseline', 'Initial Test', 'Middle Test', 'Final Test',
            'Initial Washout', 'Final Washout'};

%% Num Notes
% Plot for control subjects
figure;
hold on;
for subj_idx = Subj_C'
    skill_level = skill_NN(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NN{subj_idx, tick_idx},
                50, controlColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_NN(Subj_C,:)), 'positions', 1:6, 'colors',
        controlColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Control Subjects - NumNotes');
xlabel(['Condition']);
ylabel(['Data']);

% Plot for inverted subjects
figure;
hold on;
for subj_idx = Subj_I'
    skill_level = skill_NN(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NN{subj_idx, tick_idx},
                50, invertedColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_NN(Subj_I,:)), 'positions', 1:6, 'colors',
        invertedColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Inverted Subjects - NumNotes');
xlabel(['Condition']);
ylabel(['Data']);
scatter(x_values(tick_idx), y_values_NN{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
end
end
boxplot(cell2mat(y_values_NN(Subj_I,:)), 'positions', 1:6, 'colors', invertedColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Inverted Subjects - NumNotes');
xlabel('Condition');
ylabel('Data');

% Plot for shuffled subjects
figure;
hold on;
for subj_idx = Subj_S'
    skill_level = skill_NN(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NN{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_NN(Subj_S,:)), 'positions', 1:6, 'colors', shuffledColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Shuffled Subjects - NumNotes');
xlabel('Condition');
ylabel('Data');

% Plot combining all groups
figure;
hold on;
offset = 0.2; % Adjust the offset as needed
for subj_idx = Subj_C'
    skill_level = skill_NN(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) - offset, y_values_NN{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
for subj_idx = Subj_I'
    skill_level = skill_NN(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NN{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
for subj_idx = Subj_S'
    skill_level = skill_NN(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) + offset, y_values_NN{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
end
end
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Combined Subjects - NumNotes');
xlabel('Condition');
ylabel('Data');

% Create legend
controlLine = plot(0, 0, 'color', controlColor, 'LineWidth', 2);
invertedLine = plot(0, 0, 'color', invertedColor, 'LineWidth', 2);
shuffledLine = plot(0, 0, 'color', shuffledColor, 'LineWidth', 2);
IntermediateMarker = plot(0, 0, 'Marker', 'o', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
AdvancedMarker = plot(0, 0, 'Marker', 'x', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
ExpertMarker = plot(0, 0, 'Marker', '+', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
legend([controlLine, invertedLine, shuffledLine, IntermediateMarker, AdvancedMarker, ExpertMarker],...
    {'Control', 'Inverted', 'Shuffled', 'Intermediate', 'Advanced', 'Expert'}, 'Location', 'best');

%% NI
figure;
hold on;
for subj_idx = Subj_C'
    skill_level = skill_NI(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NI{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_NI(Subj_C,:)), 'positions', 1:6, 'colors', controlColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Control Subjects - NoteInterval');
xlabel('Condition');
ylabel('Data');

% Plot for inverted subjects
figure;
hold on;
for subj_idx = Subj_I'
    skill_level = skill_NI(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NI{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_NI(Subj_I,:)), 'positions', 1:6, 'colors', invertedColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Inverted Subjects - NoteInterval');
xlabel('Condition');
ylabel('Data');

% Plot for shuffled subjects
figure;
hold on;
for subj_idx = Subj_S'
skill_level = skill_NI(subj_idx);
marker = getMarkerSymbol(skill_level);
for tick_idx = 1:6
    scatter(x_values(tick_idx), y_values_NI{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
end
end
boxplot(cell2mat(y_values_NI(Subj_S,:)), 'positions', 1:6, 'colors', shuffledColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Shuffled Subjects - NoteInterval');
xlabel('Condition');
ylabel('Data');

% Plot combining all groups
figure;
hold on;
offset = 0.2; % Adjust the offset as needed
for subj_idx = Subj_C'
skill_level = skill_NI(subj_idx);
marker = getMarkerSymbol(skill_level);
for tick_idx = 1:6
    scatter(x_values(tick_idx) - offset, y_values_NI{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
end
end
for subj_idx = Subj_I'
skill_level = skill_NI(subj_idx);
marker = getMarkerSymbol(skill_level);
for tick_idx = 1:6
    scatter(x_values(tick_idx), y_values_NI{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
end
end
for subj_idx = Subj_S'
skill_level = skill_NI(subj_idx);
marker = getMarkerSymbol(skill_level);
for tick_idx = 1:6
    scatter(x_values(tick_idx) + offset, y_values_NI{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
end
end
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Combined Subjects - NoteInterval');
xlabel('Condition');
ylabel('Data');

% Create legend
controlLine = plot(0, 0, 'color', controlColor, 'LineWidth', 2);
invertedLine = plot(0, 0, 'color', invertedColor, 'LineWidth', 2);
shuffledLine = plot(0, 0, 'color', shuffledColor, 'LineWidth', 2);
IntermediateMarker = plot(0, 0, 'Marker', 'o', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
AdvancedMarker = plot(0, 0, 'Marker', 'x', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
ExpertMarker = plot(0, 0, 'Marker', '+', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
legend([controlLine, invertedLine, shuffledLine, IntermediateMarker, AdvancedMarker, ExpertMarker],...
    {'Control', 'Inverted', 'Shuffled', 'Intermediate', 'Advanced', 'Expert'}, 'Location', 'best');

%% NIV
figure;
hold on;
for subj_idx = Subj_C'
    skill_level = skill_NIV(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NIV{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_NIV(Subj_C,:)), 'positions', 1:6, 'colors', controlColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Control Subjects - NoteIntervalVar');
xlabel('Condition');
ylabel('Data');

% Plot for inverted subjects
figure;
hold on;
for subj_idx = Subj_I'
    skill_level = skill_NIV(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NIV{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_NIV(Subj_I,:)), 'positions', 1:6, 'colors', invertedColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Inverted Subjects - NoteIntervalVar');
xlabel('Condition');
ylabel('Data');

% Plot for shuffled subjects
figure;
hold on;
for subj_idx = Subj_S'
    skill_level = skill_NIV(subj_idx); % Extracting skill level
marker = getMarkerSymbol(skill_level);
for tick_idx = 1:6
    scatter(x_values(tick_idx), y_values_NIV{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
end
end
boxplot(cell2mat(y_values_NIV(Subject_S,:)), 'positions', 1:6, 'colors', shuffledColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Shuffled Subjects - NoteIntervalVar');
xlabel('Condition');
ylabel('Data');

% Plot combining all groups
figure;
hold on;
offset = 0.2; % Adjust the offset as needed
for subj_idx = Subject_C
    skill_level = skill_NIV(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) - offset, y_values_NIV{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
for subj_idx = Subject_I
    skill_level = skill_NIV(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_NIV{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
for subj_idx = Subject_S
    skill_level = skill_NIV(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) + offset, y_values_NIV{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
    end
end
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Combined Subjects - NoteIntervalVar');
xlabel('Condition');
ylabel('Data');

% Create legend
controlLine = plot(0, 0, 'color', controlColor, 'LineWidth', 2);
invertedLine = plot(0, 0, 'color', invertedColor, 'LineWidth', 2);
shuffledLine = plot(0, 0, 'color', shuffledColor, 'LineWidth', 2);
IntermediateMarker = plot(0, 0, 'Marker', 'o', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
AdvancedMarker = plot(0, 0, 'Marker', 'x', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
ExpertMarker = plot(0, 0, 'Marker', '+', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
legend([controlLine, invertedLine, shuffledLine, IntermediateMarker, AdvancedMarker, ExpertMarker], ...
    {'Control', 'Inverted', 'Shuffled', 'Intermediate', 'Advanced', 'Expert'}, 'Location', 'best');

%% AA
figure;
hold on;
for subj_idx = Subj_C'
    skill_level = skill_AA(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_AA{subj_idx, tick_idx},
            50, controlColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_AA(Subj_C,:)), 'positions', 1:6, 'colors', controlColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Control Subjects - AttackAngle');
xlabel('Condition');
ylabel('Data');

% Plot for inverted subjects
figure;
hold on;
for subj_idx = Subj_I'
    skill_level = skill_AA(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_AA{subj_idx, tick_idx},
            50, invertedColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_AA(Subj_I,:)), 'positions', 1:6, 'colors', invertedColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Inverted Subjects - AttackAngle');
xlabel('Condition');
ylabel('Data');

% Plot for shuffled subjects
figure;
hold on;
for subj_idx = Subj_S'
    skill_level = skill_AA(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_AA{subj_idx, tick_idx},
            50, shuffledColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_AA(Subj_S,:)), 'positions', 1:6, 'colors', shuffledColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Shuffled Subjects - AttackAngle');
xlabel('Condition');
ylabel('Data');

% Plot combining all groups
figure;
hold on;
offset = 0.2; % Adjust the offset as needed
for subj_idx = Subj_C'
    skill_level = skill_AA(subj_idx);
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) - offset, y_values_AA{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
for subj_idx = Subj_I'
    skill_level = skill_AA(subj_idx);
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_AA{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
for subj_idx = Subj_S'
    skill_level = skill_AA(subj_idx);
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) + offset, y_values_AA{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
    end
end
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Combined Subjects - AttackAngle');
xlabel('Condition');
ylabel('Data');

% Create legend
controlLine = plot(0, 0, 'color', controlColor, 'LineWidth', 2);
invertedLine = plot(0, 0, 'color', invertedColor, 'LineWidth', 2);
shuffledLine = plot(0, 0, 'color', shuffledColor, 'LineWidth', 2);
IntermediateMarker = plot(0, 0, 'Marker', 'o', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
AdvancedMarker = plot(0, 0, 'Marker', 'x', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
ExpertMarker = plot(0, 0, 'Marker', '+', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
legend([controlLine, invertedLine, shuffledLine, IntermediateMarker, AdvancedMarker, ExpertMarker], ...
{'Control', 'Inverted', 'Shuffled', 'Intermediate', 'Advanced', 'Expert'}, 'Location', 'best');
%% SK

figure;
hold on;
for subj_idx = Subj_C'
    skill_level = skill_SK(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SK{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_SK(Subj_C,:)), 'positions', 1:6, 'colors', controlColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Control Subjects - SkewAngle');
xlabel('Condition');
ylabel('Data');

% Plot for inverted subjects

figure;
hold on;
for subj_idx = Subj_I'
    skill_level = skill_SK(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SK{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_SK(Subj_I,:)), 'positions', 1:6, 'colors', invertedColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Inverted Subjects - SkewAngle');
xlabel('Condition');
ylabel('Data');

% Plot for shuffled subjects

figure;
hold on;
for subj_idx = Subj_S'
    skill_level = skill_SK(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SK{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_SK(Subj_S,:)), 'positions', 1:6, 'colors', shuffledColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Shuffled Subjects - SkewAngle');
xlabel('Condition');
ylabel('Data');

% Plot combining all groups
figure; hold on; offset = 0.2; % Adjust the offset as needed
for subj_idx = Subj_C'
    skill_level = skill_SK(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) - offset, y_values_SK{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
for subj_idx = Subj_I'
    skill_level = skill_SK(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SK{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
for subj_idx = Subj_S'
    skill_level = skill_SK(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) + offset, y_values_SK{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
    end
end
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Combined Subjects - SkewAngle');
xlabel('Condition'); ylabel('Data');

% Create legend
controlLine = plot(0, 0, 'color', controlColor, 'LineWidth', 2);
invertedLine = plot(0, 0, 'color', invertedColor, 'LineWidth', 2);
shuffledLine = plot(0, 0, 'color', shuffledColor, 'LineWidth', 2);
IntermediateMarker = plot(0, 0, 'Marker', 'o', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
AdvancedMarker = plot(0, 0, 'Marker', '+', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
ExpertMarker = plot(0, 0, 'Marker', '*', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
legend([controlLine, invertedLine, shuffledLine, IntermediateMarker, AdvancedMarker, ExpertMarker], ...
    {'Control', 'Inverted', 'Shuffled', 'Intermediate', 'Advanced', 'Expert'}, 'Location', 'best');

%% SM
figure; hold on;
for subj_idx = Subj_C'
    skill_level = skill_SM(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) - offset, y_values_SM{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
for subj_idx = Subj_I'
    skill_level = skill_SM(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SM{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
for subj_idx = Subj_S'
    skill_level = skill_SM(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx) + offset, y_values_SM{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
    end
end
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Combined Subjects - SkewAngle');
xlabel('Condition'); ylabel('Data');

% Create legend
controlLine = plot(0, 0, 'color', controlColor, 'LineWidth', 2);
invertedLine = plot(0, 0, 'color', invertedColor, 'LineWidth', 2);
shuffledLine = plot(0, 0, 'color', shuffledColor, 'LineWidth', 2);
IntermediateMarker = plot(0, 0, 'Marker', 'o', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
AdvancedMarker = plot(0, 0, 'Marker', '+', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
ExpertMarker = plot(0, 0, 'Marker', '*', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
legend([controlLine, invertedLine, shuffledLine, IntermediateMarker, AdvancedMarker, ExpertMarker], ...
    {'Control', 'Inverted', 'Shuffled', 'Intermediate', 'Advanced', 'Expert'}, 'Location', 'best');

%% SM
scatter(x_values(tick_idx), y_values_SM{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
end
end
boxplot(cell2mat(y_values_SM(Subj_C,:)), 'positions', 1:6, 'colors', controlColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Control Subjects - Smooth');
xlabel('Condition');
ylabel('Data');

% Plot for inverted subjects
figure;
hold on;
for subj_idx = Subj_I'
    skill_level = skill_SM(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SM{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_SM(Subj_I,:)), 'positions', 1:6, 'colors', invertedColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Inverted Subjects - Smooth');
xlabel('Condition');
ylabel('Data');

% Plot for shuffled subjects
figure;
hold on;
for subj_idx = Subj_S'
    skill_level = skill_SM(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SM{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_SM(Subj_S,:)), 'positions', 1:6, 'colors', shuffledColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Shuffled Subjects - Smooth');
xlabel('Condition');
ylabel('Data');

% Plot combining all groups
figure;
hold on;
offset = 0.2; % Adjust the offset as needed
for subj_idx = Subj_C'
    skill_level = skill_SM(subj_idx); % Extracting skill level
    marker = getMarkerSymbol(skill_level);
    for tick_idx = 1:6
        scatter(x_values(tick_idx), y_values_SM{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
    end
end
boxplot(cell2mat(y_values_SM(Subj_C,:)), 'positions', 1:6, 'colors', controlColor);
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Control Subjects - Smooth');
xlabel('Condition');
ylabel('Data');
scatter(x_values(tick_idx) - offset, y_values_SM{subj_idx, tick_idx}, 50, controlColor, 'Marker', marker);
end
end
for subj_idx = Subj_I'
skill_level = skill_SM(subj_idx); % Extracting skill level
marker = getMarkerSymbol(skill_level);
for tick_idx = 1:6
scatter(x_values(tick_idx), y_values_SM{subj_idx, tick_idx}, 50, invertedColor, 'Marker', marker);
end
end
for subj_idx = Subj_S'
skill_level = skill_SM(subj_idx); % Extracting skill level
marker = getMarkerSymbol(skill_level);
for tick_idx = 1:6
scatter(x_values(tick_idx) + offset, y_values_SM{subj_idx, tick_idx}, 50, shuffledColor, 'Marker', marker);
end
end
set(gca, 'XTick', 1:6, 'XTickLabel', xtlbls);
title('Combined Subjects - Smooth');
xlabel('Condition');
ylabel('Data');

% Create legend
controlline = plot(0, 0, 'color', controlColor, 'LineWidth', 2);
invertedLine = plot(0, 0, 'color', invertedColor, 'LineWidth', 2);
shuffledLine = plot(0, 0, 'color', shuffledColor, 'LineWidth', 2);
IntermediateMarker = plot(0, 0, 'Marker', 'o', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
AdvancedMarker = plot(0, 0, 'Marker', 'x', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
ExpertMarker = plot(0, 0, 'Marker', '+', 'MarkerEdgeColor', 'k', 'MarkerFaceColor', 'k');
legend([controlLine, invertedLine, shuffledLine, IntermediateMarker, AdvancedMarker, ExpertMarker], ...
    {'Control', 'Inverted', 'Shuffled', 'Intermediate', 'Advanced', 'Expert'}, 'Location', 'best');

function marker = getMarkerSymbol(skill_level)
% Define marker symbols for each skill level
if skill_level == 1
    marker = 'o'; % Intermediate
elseif skill_level == 2
    marker = 'x'; % Advanced
elseif skill_level == 3
    marker = '+'; % Expert
else
    marker = 'o'; % Default marker
end