Understanding the Influence of Electrical Muscle Stimulation on Motor Learning: Enhancing Motor Learning or Disrupting Natural Progression?

Steeven Villa
LMU Munich
Munich, Germany
villa@posthci.com

Finn Jacob Eliyah Krammer
LMU Munich
Munich, Germany
finn.krammer@campus.lmu.de

Yannick Weiss
LMU Munich
Munich, Germany
yannick.weiss@lmu.de

Robin Welsch
Aalto University
Espoo, Finland
robin.welsch@aalto.fi

Thomas Kosch
HU Berlin
Berlin, Germany
thomas.kosch@hu-berlin.de

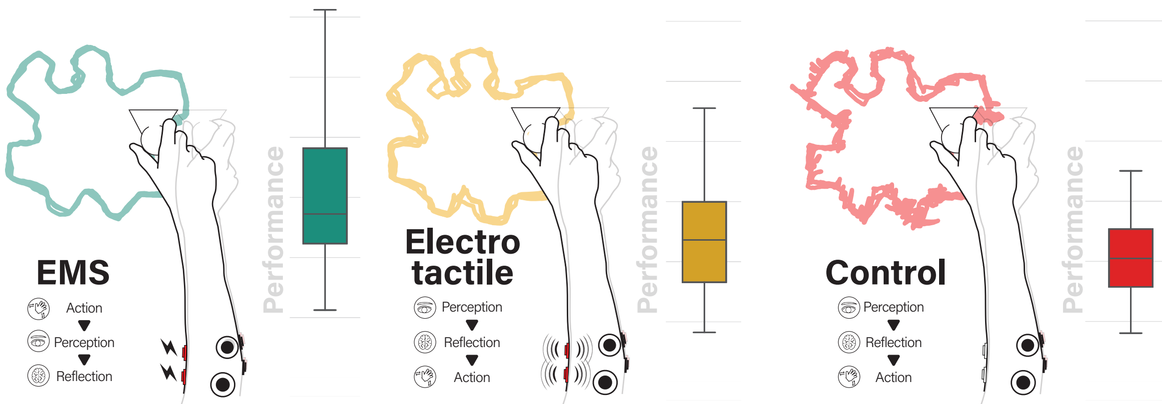

Figure 1: In this paper, we compared Electrical Muscle Stimulation (EMS) and electrotactile feedback against a no feedback control condition for evaluating motor learning consolidation. Our results show that EMS enhances motor skill acquisition despite a lower initial learning rate.

Abstract

Electrical Muscle Stimulation (EMS) induces muscle movement through external currents, offering a novel approach to motor learning. Researchers investigated using EMS as an alternative to conventional non-movement-inducing feedback techniques, such as vibrotactile and electrotactile feedback. While EMS shows promise in areas such as dance, sports, and motor skill acquisition, neurophysiological models of motor learning conflict about the impact of externally induced movements on sensorimotor representations. This study evaluated EMS against electrotactile feedback and a control condition in a two-session experiment assessing fast learning, consolidation, and learning transfer. Our results suggest an overall positive impact of EMS in motor learning. Although traditional electrotactile feedback had a higher learning rate, EMS increased the learning plateau, as measured by a three-factor exponential decay model. This study provides empirical evidence supporting EMS as a plausible method for motor augmentation and skill transfer, contributing to understanding its role in motor learning.

CHI '25, Yokohama, Japan

ACM ISBN 979-8-4007-1394-1/25/04
https://doi.org/10.1145/3706598.3714183

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**.

Keywords

Electrical Muscle Stimulation, Motor Learning, Learning Effects

ACM Reference Format:
Steeven Villa, Finn Jacob Eliyah Krammer, Yannick Weiss, Robin Welsch, and Thomas Kosch. 2025. Understanding the Influence of Electrical Muscle Stimulation on Motor Learning: Enhancing Motor Learning or Disrupting Natural Progression?. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 17 pages. https://doi.org/10.1145/3706598.3714183

1 Introduction

The human nervous system learns and refines motor movements through repetition, enabling humans to acquire motor skills when repeating a particular movement over and over again [33]. However, motor acquisition is not trivial, requiring humans to repeat their actions in a trial-and-error fashion [8]. Although the multiple repetitions of motor movements may enhance the skill acquisition of other motor tasks [65], many task-specific repetitions are still necessary to observe learning effects. To speed up learning new motor skills, researchers in Human-Computer Interaction

(HCI) have turned their attention to wearable haptic devices. In this context, Electrical Muscle Stimulation (EMS) [44] emerged as an explicit feedback modality for motor skill training. EMS is a noninvasive technology that activates muscles by small electrical currents through electrodes attached to the user's skin. Extensively researched in the medical field, EMS has shown significant benefits in health, well-being, and muscle recovery therapy. Evidence supports that EMS offers advantages such as muscle strengthening, pain relief, and enhanced recovery, setting EMS as a potential technology to support motor activities [53].

In the field of HCI, EMS has gained recognition as a powerful explicit feedback mechanism, enhancing user experiences across various domains such as Virtual Reality (VR) and Augmented Reality (AR) [79], sports training [22], gaming [55], music, and communication applications [57] (for a comprehensive review, see Faltaous et al. [15]). This broad applicability has inspired a wide range of innovative uses. Notably, EMS has been applied to support tasks such as navigation [59], redirected walking [3], skill acquisition [12, 36], posture correction in sports [14], and exergames [56]. Additionally, studies have shown that prolonged use of EMS can lead to measurable improvements in reaction time [27] and dexterity [73]. EMS has frequently been applied in HCI research to support motor skill acquisition, as it provides clear and actionable feedback and can guide user movements via external actuation [15]. Zhou and Segawa [85] used EMS to improve hand-eye coordination, while Faltaous et al. [13] applied it to golf training, focusing on swing correction. Similarly, Niijima [47] showed that EMS improves temporal accuracy in motor tasks. In more complex motor skills, Tamaki et al. [74] developed an EMS system for learning finger-based languages, and Nishida et al. [50] speculated it could aid in acquiring time-sensitive skills through enhanced kinesthetic feedback.

Yet, motor learning frameworks [10, 18, 61, 69, 80] emphasize that awareness, agency, and reflection are essential. Previous research suggests that externally actuating users during learning, as with explicit EMS feedback, only provides short-term motor skill acquisition [75]. Simultaneously, prior work suggested that feedback methods, such as vibrotactile or electrotactile feedback, can be used for reflection rather than actuation, thus aligning better with these frameworks to support motor learning. For example, evidence suggests that vibrotactile haptic feedback positively contributes to motor learning [24, 29, 72]. Therefore, it is essential to examine the friction between recent empirical findings on EMS for motor skill transfer in HCI and established motor learning frameworks from neurological research [10]. Investigating this relationship can provide the basis for more effective EMS feedback in motor learning and offer valuable insights for interpreting EMS study outcomes within these frameworks.

In this paper, grounded on Doyon et al. [10] model for motor learning, we investigate the contributions of explicit EMS feedback to motor learning through a between-subjects lab study. Thirty-six healthy volunteers were randomized into EMS, Electrotactile stimulation, or a Control group. The study spanned two sessions, with two training blocks and four assessments. Our findings show that EMS improved motor skills immediately after training, positioning it as a strong candidate for augmenting motor skills. This effect extended into the consolidation phase, contributing to both motor skill retention and transfer. While Electrotactile feedback resulted in a higher learning rate, EMS achieved a higher absolute learning gain, as learning through Electrotactile feedback reached a plateau earlier than EMS. This paper, therefore, provides empirical evidence on how and at which stages EMS supports motor learning compared with typical feedback modalities and practicing without any feedback.

2 Related Work

We investigated relevant literature regarding EMS, EMS for interactive systems, and foundations of motor learning [67].

2.1 Electrical Muscle Stimulation

EMS is a technique that uses electrical impulses, delivered through skin electrodes, to stimulate muscle contractions [5, 19]. EMS was designed to aid motor function recovery by mimicking the brain's natural signals to trigger muscle activity. EMS sends controlled electrical impulses through electrodes on the skin, replicating the nervous system's signals to initiate muscle contractions. These impulses activate motor neurons, causing the muscle fibers to contract. By adjusting the intensity, frequency, and duration of the impulses, EMS can be tailored to strengthen muscles, improve endurance, enhance recovery, or reduce tension. This process bypasses the brain's direct control, simulating voluntary muscle contractions [31]. Different intensities and frequencies have different effects on the perceived stimulation. Moreno-Aranda and Seireg [45] showed that high-frequency alternating current signals trigger powerful muscle contractions with minimal discomfort, for example, when treating paraplegic or quadriplegic patients. In this context, EMS expanded to rehabilitation and medical settings [54] or support fitness training [77]. In rehabilitation, EMS helps prevent muscle atrophy and promotes muscle re-education, while athletes use it to enhance strength and endurance [60]. Recently, EMS has gained significant traction in HCI research to provide feedback and steer the physical movements of users [58].

2.2 EMS for Motor Augmentation and Learning in HCI

Over the past decade, EMS has emerged as a fundamentally different interaction modality to methods such as auditory, vibrotactile, or visual cues [15]. Unlike these conventional interfaces, EMS allows for direct manipulation of body movements. For example, Pfeiffer et al. [59] explored how EMS could support user navigation. By electrically stimulating the sartorius muscle, they induced leg rotation during the swing phase, though users retained enough control to counteract the movement as needed. Extending this work, Auda et al. [3] created an infinite walking experience VR by manipulating users' leg movements through EMS, causing them to walk in circles in the physical world while maintaining a straight path in the virtual environment.

EMS has also been explored as a technique for motor augmentation and learning; notable examples include improving hand dexterity. Takahashi et al. [73] enhances finger control by enabling independent EMS flexion of each finger, addressing the limitations of often triggering unwanted movements in adjacent fingers.

In a complementary approach, Nith et al. [52] enhance EMS performance by incorporating mechanical brakes to control finger positions and prevent unintended movements. This solution increases the independence of finger joints and reduces oscillations, further expanding EMS applications in areas such as fingerspelling and VR-based interactions.

Furthermore, EMS has been employed to enhance users' reaction times while maintaining their sense of agency. Kasahara et al. [26] investigated preemptive force-feedback systems, such as EMS, for tasks such as drumming, addressing a common issue: preemptive guidance often reduces the user's sense of agency. The authors discovered that applying EMS within 160 ms of a visual cue reduced reaction times by 80 ms without compromising agency. A follow-up study confirmed this timing strategy significantly enhanced users' perceived control compared to existing EMS-based systems. In later work, Kasahara et al. [27] examined whether reaction time improvements from EMS persisted after its removal. They found that the EMS condition led to a lasting reduction in reaction time (8 – 20 ms) after EMS was removed, suggesting immediate benefits in performance augmentation. Similarly, Nishida et al. [50] used EMS to synchronize muscle activity between two individuals, enabling quicker responses than those prompted by visual stimuli. While visual responses typically take about 250 milliseconds, the EMS system detected muscle activity in one person and triggered a corresponding movement in another within approximately 60 milliseconds. Some participants even reported feeling as though they initiated the movement themselves.

EMS was explored to improve sports performance. Faltaous et al. [14] studied an EMS system to help crossminton players maintain the ready position. They compared EMS and vibrotactile feedback. The results indicated that the EMS system enabled coaches to guide players in real-time, which could potentially reduce delays in skill acquisition. Other sports, such as golf, have also benefited from EMS, where it has been used to correct the hit angle during putting [13]. The potential of EMS to facilitate motor learning has been hypothesized in various studies. For example, Hassan et al. [22] suggested that EMS could enhance motor learning for foot strikes. Additionally, EMS has been used to assist users in performing rhythmic patterns [11, 12] and tremolos on the piano [49]. However, these studies did not investigate the learning effects of EMS across multiple training sessions, leaving the effectiveness of EMS in fostering motor learning inconclusive. Also, Niijima et al. [48] investigated EMS-supported piano techniques, finding improved efficiency for certain playstyles, yet no empirical evidence of learning effects beyond a motor skill augmentation.

Overall, EMS is a technique used to enhance motor skills by directly influencing physical movements, with applications in areas such as sports performance, navigation [59], virtual reality [3], and improving dexterity [73]. However, prior research has primarily evaluated the benefits of EMS within a single session or without accounting for the effects of a sleep session in between, leaving its contribution beyond this learning largely unexplored. While some studies suggest that EMS may facilitate motor learning in specific contexts [11, 12, 22, 48–50], there is still a considerable gap in exploring its learning effects beyond performance enhancement while using the technology.

2.3 Neural Basis of Motor Learning

Motor skills are developed through different cognitive stages [64], with information moving from short-term to long-term memory, which includes explicit and implicit types [7]. Long-term memory is the brain's ability to store and retrieve information over extended periods, ranging from days to a lifetime, enabling learning, retention, and knowledge consolidation. Explicit memory is conscious, while implicit memory is not, and it is challenging for individuals to articulate it in detail. In motor skill learning, explicit memory forms in the early stages and is later consolidated into implicit memory, requiring less conscious attention. Motor skills can be retained for years. Various models explain the neurobiological processes behind implicit memory storage [10, 17, 30, 37, 41] and brain region contributions during learning [82], such as the medial temporal lobe in fast learning and cortical motor regions in slow learning. Among the various motor learning models studied, the framework proposed by Doyon et al. [10] is particularly relevant to our research. This model outlines five phases of motor skill acquisition and retention: (1) **Fast (early) learning**, where rapid improvements occur; (2) **Slow (later) learning**, characterized by gradual performance gains; (3) **Consolidation**, during which learned skills are stabilized; (4) The **automatic phase,** where skilled behavior becomes more effortless and consistent; and (5) **Retention**, which describes the maintenance of skills after long periods without practice.

The **fast (early) learning phase** is characterized by significant improvements in motor behavior. This stage requires high levels of attention and generates substantial cognitive workload, especially when a task is encountered for the first time [68]. Fast learning is typically observable from the first session, and research shows that proper feedback provides significant benefits during this phase [83]. Additionally, error correction plays a critical role in early learning, being more important at this stage than in later phases [41].

The slow learning phase, spanning multiple sessions, is characterized by a deceleration in progress as motor skill performance stabilizes and becomes more consistent. Motor learning is inherently time-dependent, with **consolidation** serving as an intermediate process between practice sessions. During this phase, explicit knowledge of the motor skill transitions into implicit memory. Notably, evidence suggests that sleep plays a crucial role in motor memory consolidation [10, 39, 81]. Beyond sleep, factors such as interest, motivation, attentiveness, vigilance, and levels of distraction also significantly influence how well a memory is retained [7, 38]. **Motor consolidation** is key to embedding the skill into the body's memory, eventually leading to the **automatic execution phase**. This last stage occurs when the task can be performed without conscious effort, indicating that the motor skill has become automatic. **The retention phase** is achieved when this skill can be recalled after a significant period without practice, remaining intact in long-term memory.

Most HCI studies on motor learning primarily focus on the fast-learning phase. A variety of interfaces have been proposed to support motor learning during this phase, often through augmented feedback mechanisms, such as vibrotactile feedback. These mechanisms aim to enhance awareness of movements and errors, supporting reflection and adjustment. Such approaches fit coherently within motor learning frameworks, as they improve awareness by providing additional information, enabling users to reflect on their actions, adjust motor behavior, and thus learn more effectively.

2.4 EMS Action Planning and Execution in HCI

Faltaous et al. [15] states that the action-perception-reasoning and perception-reasoning-action models describe two fundamentally different interaction paradigms in HCI, particularly relevant to systems including EMS. Drawing on Dourish [9] work, they state that in the perception-reasoning-action model, which aligns with traditional interaction paradigms, the flow begins with perception: the user first perceives information, engages in reasoning to interpret and plan a response, and then executes an action accordingly. This process is often seen in conventional interfaces, such as vibrotactile cues or visual notifications, where users observe cues, decide on their response, and act upon them. In contrast, the action-perception-reasoning model represents a paradigm shift introduced by EMS systems. Here, action is initiated before conscious perception or reasoning, as the EMS system directly actuates the user's muscles to produce movement. This inversion of the traditional sequence means that users first experience an action (e.g., their arm moving involuntarily), which they perceive and cognitively interpret to understand its purpose or intention.

3 Experimental Design and Hypotheses

EMS introduces a new paradigm by reversing the typical motor learning sequence. Traditional approaches focus on deliberate practice and user adjustments [78], following a perception-reasoning-action cycle. However, EMS-augmented actions occur before reflection, in the order of action, perception, and reasoning [15]. This can hinder reflective practice and sensorimotor learning Proteau et al. [61]. For example, Tatsuno et al. [75] found that participants trained with EMS in a wrist rotation task compensated for EMS-induced movements after removing stimulation, although this compensatory effect diminished over time. Similarly, Nishikawa et al. [51] recently found that EMS use during hand gesture learning led to higher errors.

We operationalized motor learning through the Mirror Drawing (MD) task across two distinct sessions, a common task that has been employed in previous research [28, 62, 70]. The MD task measures motor learning through both within-session performance (Post-Training 1 and 2 Assessments - **fast learning phase**) and across-session performance (Consolidation Assessment - **consolidation phase**). We assessed learning using two metrics: (1) the distance traced within a fixed time and (2) the total time to trace a complete shape. Participants show motor learning by tracing longer distances in the given time and completing shapes faster. To examine learning transfer, we introduced an unfamiliar shape at the end of the second session, evaluating the participants' ability to apply their acquired motor skills to a new context. To assess learning rates and gains, we use an exponential decay model. Based on this experimental design and in light of previous work, we derived the following hypotheses:

H1 There will be a performance difference between the Electrotactile, EMS, and Control conditions during the motor learning task, with Electrotactile showing better results than the Control and EMS conditions.

- *We expect a similar, though less pronounced, effect on within-session performance. During the initial phase, motor adaptation is still occurring, and both Electrotactile and EMS have shown potential benefits at this stage. However, Electrotactile feedback is more established and likely to provide more consistent improvements.*

H2 Electrotactile stimulation will result in significantly better motor skill consolidation performance compared to both EMS and the Control condition.

- *This is because it does not interfere with the sensorimotor representation during the task and aligns with the traditional training sequence of perception, reflection, and action.*

H3 Learning rate will be higher with Electrotactile stimulation compared to EMS, as indicated by the α parameter of the exponential decay model.

- *We anticipate that these factors will influence not only the amount an individual learns but also the speed at which they acquire new skills.*

H4 Electrotactile stimulation will lead to greater overall learning, as measured by the A parameter of the exponential decay model, compared to both EMS and the Control condition.

- *Electrotactile feedback provides individuals with additional sensory information related to the task, allowing them to form a more accurate sensorimotor representation based on both perception and reflection.*

H5 The EMS condition will show significantly lower performance in the learning transfer task compared to the Control group.

- *Since sensorimotor representations play a critical role in consolidating motor skills, we hypothesize that a weaker sensorimotor representation will limit the ability to transfer learned skills to a new context.*

Having these hypotheses, we tested the following conditions, following the procedure outlined in Figure 2:

- **EMS**: Participants in this group received Kinaesthetic EMS feedback. This type of feedback provides electrical impulses that stimulate muscle contractions. Thereby applying a corrective movement in the correct direction through participant's muscle exertion.
- **Electrotactile**: Participants in the Electrotactile group received electrotactile feedback. This approach involves the delivery of electrical stimuli directly to the skin to create vibration sensations without inducing muscle contractions.
- **Control**: The Control group did not receive any form of haptic feedback. This group served as a baseline to compare the effects of the two haptic feedback methods against no feedback at all.

3.1 Participants

A total of 36 participants (N = 36; 14 males, 20 females, 2 non-binary) participated in this study, each completing two sessions, resulting in 72 sessions. The participants had an average age of 25 years (M = 25.91, SD = 4.86). This sample size aligns with those typically employed in motor learning research [1, 2, 4, 6, 28, 62] and EMS studies [15]. Participants were compensated €6 per 30 minutes of participation. Each participant attended two sessions on

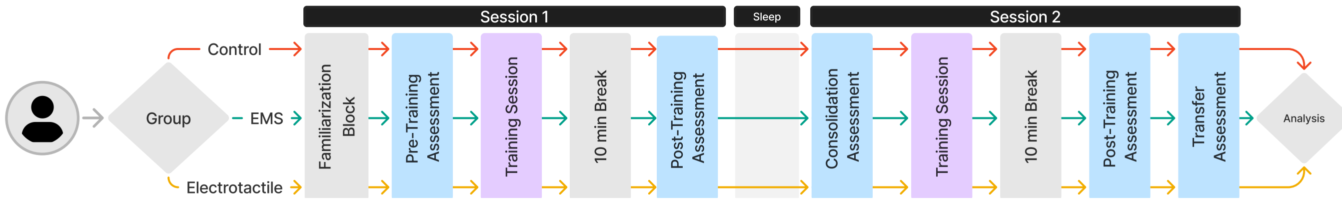

Figure 2: Procedure of the experiment. Our participants were assigned to their condition and got familiarized with the setup and task. Then, the participants started with the first assessment, a break, and a second assessment. After a long-term break, participants participated in a third and fourth session. Finally, we assessed transfer learning using a transfer assessment.

separate days, with an average interval of 6 days between sessions (M = 6.73, SD = 4.60). No significant differences were observed between groups regarding the time between sessions. Each session lasted approximately 75 minutes, totaling 2.5 hours per participant. Participation was voluntary, and participants were informed that participation could be terminated.

Group Allocation Check: **1. Self-reports:** To control for potential effects of group allocation, we collected data on participants' dominant hand and their drawing skills, measured by the average hours spent drawing per week (self-reported). Additionally, we gathered information on the average hours spent playing video games per week (self-reported). Out of all participants, two reported being left-handed, and they were assigned to different groups; previous work revealed that left-handed individuals did not significantly differ from right-handed individuals in the MD task [4]. As the hours per week self-reported data was found not to be normally distributed, we conducted a Kruskal-Wallis test to determine if there were statistically significant differences between the distributions of Control, EMS, and Electrotactile groups. The test did not show a statistically significant difference between the groups for hours drawn per week $H(2) = 0.593$, $p = 0.743$, nor for hours playing games $H(2) = 0.059$, $p = 0.970$. **2. Pre-training Performance:** Additionally, to control for a priori motor skills of participants, we assessed performance before the first training session consisting of three trials. We conducted a Kruskal-Wallis test to compare the means of Control, EMS, and Electrotactile groups. The analysis showed that there was no statistically significant difference between the groups, $H(2) = 4.38$, $p = 0.112$. These results suggest that the differences between groups at the start of the experiments are not significant and provide a ground for further statistical differences to be influenced by the interventions made during the sessions.

3.2 Experimental Design

We conducted a between-subjects study to evaluate the effectiveness of the different haptic feedback methods mentioned above. Participants were randomly assigned to one of three experimental groups: the EMS group, the Electrotactile group, and the Control group. The study consisted of two sessions; each session involved two assessment stages (i.e., at the beginning and 10 minutes after the training session) and a training session; each training session involved 30 trials, while the assessment involved three trials each. Additionally, the first session included a familiarization stage for the participants to understand and ask about the task and the setup. The last session included a Learning Transfer Test stage for assessing how well participants transfer the knowledge to a different shape.

3.3 Feedback Rendering

The feedback was rendered using an FDA-approved Sanitas 41 generator connected to a "Let Your Body Move" toolkit [58]. We used Axion EMS/TENS 32mm diameter round electrodes for easier placement and muscle targeting. The electrodes were adhesive and adhered to the user's arm.

3.3.1 EMS Feedback. In this condition, EMS was applied to participants' arms to provide explicit kinaesthetic feedback, guiding them to correct their movements. The feedback was designed to influence muscle contractions, helping participants stay on the intended path without overshooting and avoiding additional corrections. Therefore, corrective actuation was triggered whenever participants deviated from the specified path, which is a common approach in HCI research on motor skill transfer and learning using EMS [13, 14, 22, 27]. The frequency and pulse width of the EMS were set to 150 Hz and $100\mu s$, respectively, and the intensity was calibrated before the study.

3.3.2 Electrotactile Feedback. In this condition, electrotactile stimulation was applied through the same set of electrodes that participants in the EMS group received feedback. Participants in this group received electrical pulses directly to the skin, which created a tingling sensation. The stimulation intensity was adjusted to be noticeable, but without exerting any movement on the participant, the electrode location was similar to that of the EMS group. This type of feedback is analogous to explicit vibrotactile feedback, which serves as a notification indicating that a correction is necessary. Yet, it does not actuate the participants' bodies but makes them aware and lets them correct themselves; this type of feedback is also typical in HCI [22, 76].

3.3.3 Electrode Placement. To achieve control of two-dimensional movement in the vertical plane, we focused on four key muscle groups at the forearm, the most common location for EMS actuation in HCI [15] that facilitate wrist motion. Radial deviation (leftward movement) is controlled by the Extensor Carpi Radialis (ECR), while Ulnar deviation (rightward movement) is driven by the Extensor Carpi Ulnaris (ECU). Wrist flexion (downward movement) is primarily managed by the Flexor Carpi Ulnaris (FCU), and wrist extension (upward movement) is enabled by the Flexor Carpi Radialis (FCR) [35, 84]. We selected the electrode placement following the setup

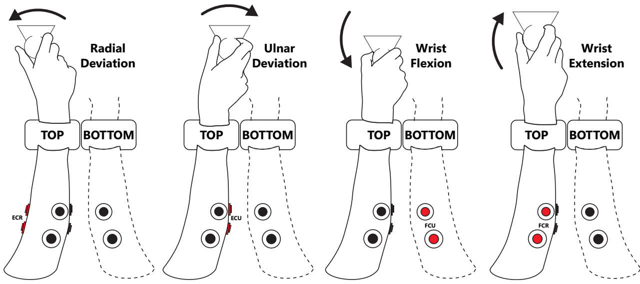

Figure 3: Illustration of wrist movements and associated muscle activations. Radial deviation (left) is facilitated by the Extensor Carpi Radialis (ECR), while Ulnar deviation (right) is driven by the Extensor Carpi Ulnaris (ECU). Wrist flexion (downward movement) is primarily controlled by the Flexor Carpi Ulnaris (FCU), and wrist extension (upward movement) is enabled by the Flexor Carpi Radialis (FCR). The diagram indicates the specific muscle groups responsible for each directional movement

described by Lopes et al. [36], effectively supporting this range of motion. The specific electrode placements are illustrated in Figure 3. For more detailed information on the electrode placement, we refer to [36, 42].

3.3.4 Control. Participants in the Control group received no feedback while performing the task. They completed the task without any external cues, relying solely on their proprioception and observation.

3.4 Mirror Drawing Task

The MD task, a well-established method for studying skill learning since 1910 [28, 62, 70], involves participants tracing a shape (typically a polygon, such as a star, diamond, square, or triangle) while remaining within the boundaries of a double line. The key challenge is that participants can only see an inverted reflection of their hand through a mirror or, in modern setups, a mirrored input mapped in the screen. This setup allows researchers to study how new associations are formed between visual input and corresponding arm movements [43].

The MD task utilized in this experiment is an implementation of the original MD task by Snoddy [69], further developed by Stratton et al. [71], and more recently adapted for delta robot input by Sullivan et al. [72]. In this experiment, participants were asked to repeatedly trace an abstract shape displayed on a computer monitor as quickly and accurately as possible. They interacted with the system using a Novint Falcon delta robot, with position data sampled at 200 Hz. A stiff virtual spring was applied along the Falcon's third degree of freedom (DOF) to constrain movement to a vertical plane parallel to the computer screen. This setup ensured that the horizontal and vertical movements of the Falcon were directly translated to the corresponding movements of the on-screen cursor. However, the horizontal axis was inverted: moving the Falcon to the left caused the cursor to move right, and vice versa.

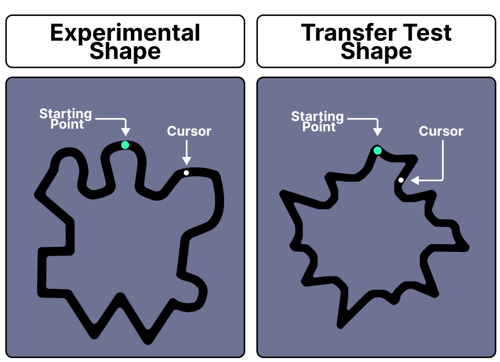

Figure 4: Shapes used in the MD task. Left: Shape extracted from [72] and used in the main experiment. Right: Shape generated for the transfer test. The starting point was the same as the endpoint and was depicted in the interface as a green point; the participant cursor was displayed as a withe circle.

Shape Selection. In this study we used two shapes in the MD task; First, a *Test Shape:* In previous research, Saqures or star shapes have often been used in the MD task due to their simplicity [4, 6, 25, 28]. Yet, for healthy users, this shape can be overly simple in healthy adults. To introduce a higher level of complexity for our experiment, we selected a shape that has been validated in the literature as sufficiently complex within the context of motor learning [72]. Second, for *Motor Transfer*, we needed a shape that participants had not encountered before [6]. Consequently, we designed a new geometrically irregular shape. Both shapes are illustrated in Figure 4.

3.5 Apparatus

The experimental setup utilized a Novint Falcon device for input, constrained to two dimensions, allowing users to move the robot's end-effector within a 2D plane, similar to the setup described by Sullivan et al. [72]. The device was connected to a Dell G5 laptop running Windows 11, and the experiment was programmed using Unity 3D version 2024.1. To provide different feedback modalities, we used two FDA-approved EMS signal generators (Sanitas 41) and two "Let Your Body Move" toolkits, initially reported by Pfeiffer et al. [58]. This configuration allowed us to utilize four EMS channels. Additionally, a Manfrotto armrest was employed to prevent participant fatigue and minimize using non-target muscles during the task. The complete setup is illustrated in Figure 5.

3.6 Calibration Procedure

We first focused on the muscle groups mentioned above for the calibration procedure. The participants were instructed to tense the target muscle in the desired direction, and the experimenter positioned two electrodes in the skin over the muscle. The EMS device was then incrementally adjusted, increasing the intensity step by step until either movement was observed or the participant reported mild discomfort.

Once the movement was successfully induced, we transitioned to the computer, where the calibration scene was prepared. We initially set the EMS generator to the intensity at which movement was first

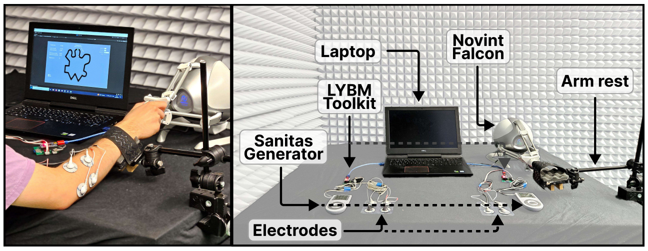

Figure 5: Left, User performing the experimental task. Right, Experimental setup featuring a Novint Falcon device constrained to one dimension for input, connected to a Dell G5 laptop running Windows 11, and programmed using Unity 3D version 2024.1. Feedback modalities were provided using FDA-approved EMS signal generators and "Let Your Body Move" toolkits, utilizing four EMS channels. A Manfrotto armrest was employed to prevent participant fatigue and ensure proper muscle usage.

observed. The participant's arm was then positioned and secured using the armrest. They moved the mouse to center the cursor on the screen, where a green circle appeared at the start of the test. After informing the participants of the upcoming stimulation, they were instructed to remain still while the EMS was active.

When the participant kept the cursor inside the green circle for 3 seconds, the target muscle was stimulated for one second, after which the EMS was deactivated. This process allowed us to assess the effect of EMS on wrist movement under experimental conditions. If the movement was too pronounced or absent, the intensity was adjusted accordingly. The goal was to achieve minimal yet observable movement to avoid overcorrections during the task.

The procedure for the electrotactile group was identical; however, in this case, the stimulation intensity was gradually increased until participants could perceive the feedback without inducing any movement. After the electrodes were placed, the participant's hand was placed on the armrest, with their hand in the grip; the experimenter gradually increased the intensity until the participant reported they could clearly identify the feedback.

3.7 Experimental Procedure

Participants attended two experimental sessions. Upon arrival at the first session, they were informed about the study's purpose and provided with an informed consent form. Participants were informed of their right to withdraw from the study without explaining or impacting their compensation. After providing consent, each participant was randomly assigned to an experimental group and seated before a screen. Feedback calibration was performed, and their arm was positioned on the armrest with the elbow resting on the table. The chair height was adjusted for comfort, and the armrest was positioned to support the arm and prevent fatigue, ensuring minimal muscle use during the task. The distance from the Novint Falcon device was also adjusted for comfortable wrist movements.

We explained the MD task to the participants and instructed them to complete the trials "as fast and accurately as possible," following the practice from previous studies [6, 72]. They were given three practice trials without feedback to familiarize themselves with the setup and could ask questions before beginning the experiment. Once the participant confirmed their understanding, they completed a 3-trial pre-intervention motor skills assessment. This and all subsequent assessments were conducted without feedback across all groups.

Following the assessment, the first training session began, consisting of 30 trials with feedback provided based on the participant's group. After the training session, participants took a 10-minute break before performing a second assessment. The first session concluded afterward, and participants were dismissed.

In line with motor learning theory, which emphasizes the importance of sleep for consolidation [39], participants returned for the second session after at least one night of sleep. The second session began with a third assessment and another training session with group-specific feedback. After a 10-minute break, participants completed a fourth assessment and a motor transfer test using a different MD shape. Participants completed NASA-TLX [21] and System Usability Scale [34] assessments during both sessions. An overview of the experimental process is illustrated in Figure 2.

3.8 Measures

In this study, we investigate the impact of EMS feedback on motor learning using the well-established MD task [6]. This task is frequently used to assess motor learning, with two notable variations: measuring the time after completing a fixed length (i.e., time to trace the full shape) [28, 32, 72] or path length/number of shapes achieved within a fixed timeframe [40, 66, 86]. We analyze both metrics across the three primary motor learning assessments (Post-training assessments 1 and 2 and Consolidation assessments) and during a motor transfer assessment conducted in the second session. The following section provides detailed descriptions of these measures.

3.8.1 Path Length: We measured the distance a participant could accurately trace along a shape's path in 5 seconds. The metric reflects the path length, adjusting for errors where the tracing deviates outside the shape's boundaries. Only correctly traced portions within the borders and in the clockwise direction are counted, with higher values indicating better performance.

3.8.2 Total Time: The total time, measured in seconds, that a participant takes to complete a shape. This metric indicates the efficiency of the participant's performance, with shorter completion times being better.

3.8.3 Path Exits: The number of times a participant crosses the boundaries of the shape, specifically when they leave the main body of the shape, is counted. However, the times when the participant re-enters the shape are not included in this count.

3.8.4 Learning Assessments: To evaluate motor learning in participants, we assessed their motor skills using the metrics outlined above (Path Length, Total Time, and Path Exits) at different time points: after each training session (Post-Training), and after learning consolidation at the beginning of the second session. All assessments were conducted without providing any feedback across the three groups.

- **Post-Training 1:** This assessment took place 10 minutes after the training trials at the end of the first session. It evaluates motor learning during the Fast Learning stage. A significant performance improvement is expected compared to the Pre-training assessment.
- **Post-Training 2:** A similar assessment was conducted at the end of the second session. As with Post-Training Performance 1, a substantial performance improvement is expected compared to the Pre-training assessment.
- **Consolidation:** This assessment occurred at the beginning of the second session, after participants had completed the first training session and had a night of sleep but before undergoing any further training. This session evaluates the consolidated motor skills in the Slow Learning phase. While performance is expected to be better than the Pre-training assessment, it may not surpass the Post-Training assessment, as participants rely on the knowledge consolidated from the previous session, which may not encompass all the gains achieved during the session.

3.8.5 Motor Transfer Assessment. To evaluate the generalizability of the acquired motor knowledge to different motor tasks, we performed a motor transfer assessment, consisting of the Mirror Tracing task with a previously unseen shape.

3.8.6 Learning Rate. We employed an exponential decay function with an asymptote to model the learning across the three feedback groups [80]. Exponential decay models are frequently used to quantify learning rates in motor learning processes [23, 63]. We fitted a three-parameter model to the training data from both sessions in sequence to capture this learning process. Specifically, we concatenated the trials from both training sessions, allowing us to account for trial-level learning throughout the training period. The fitted model was initially proposed by Newell and Rosenbloom [46], which is the following:

$$E(RT) = A + Be^{-\alpha N} \quad (1)$$

Where $E(RT)$ is the expected value of the Response Time (RT) under evaluation on practice trial N; A is the expected value of the RT after practice has been completed (asymptote parameter). This parameter can also be viewed as the minimum response time that can be achieved after all the practice trials; B is the change in the expected value of the RT from the beginning of practice to the end of practice (change score parameter); α is the exponential learning rate parameter [80].

3.8.7 Additional Measures: We assessed the perceived usability of the system using the System Usability Scale (SUS). While the SUS was initially developed for evaluating software usability, it has been widely adopted as a standardized and validated tool for assessing the usability of diverse technologies, including those involving sensory feedback. In this context, SUS was chosen for its ability to provide a consistent and comparative evaluation of the user experience across the two feedback conditions including EMS and electrotactile feedback. Although SUS does not capture domain-specific aspects of motor learning, it complements the empirical performance metrics by offering insights into user comfort and system integration. Participants completed the SUS questionnaire after the study. We also measured task load using the NASA Task Load Index (NASA-TLX [21]). Participants filled out the NASA-TLX questionnaire at the end of each session.

4 Results

To determine the appropriate statistical tests for analyzing the variable of interest, we first assessed the normality of the data using the Shapiro-Wilk test across all groups. For each group, we computed the test statistic and the corresponding p-value. If all groups were found to be normally distributed ($p > 0.05$), we proceeded with a one-way ANOVA to evaluate the differences between the groups, followed by Tukey's Honest Significant Difference (HSD) test for post-hoc analysis in cases where a significant effect was observed. However, if at least one group violated the normality assumption ($p < 0.05$), we employed the non-parametric Kruskal-Wallis test instead. When the Kruskal-Wallis test indicated a statistically significant difference between groups, Dunn's post-hoc test with Bonferroni correction was used for pairwise comparisons.

4.1 Path Length

We evaluated the Path Length across the three main assessments: *Post-Training 1*, *Consolidation*, and, *Post-training 2* across the three experimental conditions (Control, EMS, and Electrotactile). We report the results in the following.

Post-Training 1. To evaluate differences in Path Length in the Post-Training 1, we conducted a Kruskal-Wallis test, as the data did not meet the normality assumptions required for parametric tests. The test revealed a statistically significant difference between the groups, $H(2) = 6.51$, $p = .03$. Subsequent pairwise comparisons using Dunn's post-hoc test with Bonferroni correction indicated that the EMS condition significantly outperformed the Control condition ($p = .03$). No statistically significant differences were found between the other pairs (all $p > .05$). The performance ranking, based on mean values, suggests that participants in the EMS group (M = 4.51, SD = 1.84) achieved the highest performance, followed by the Electrotactile group (M = 3.59, SD = 1.22), and the Control group (M = 3.45, SD = 1.82). These results indicate that the EMS feedback led to longer path length compared to the Control feedback (see Figure 6 for an overview).

Consolidation. We conducted a Kruskal-Wallis test to evaluate Path Length in the Consolidation assessment. The test did not reveal a statistically significant difference in *Path Length* between the Control, EMS, and Electrotactile groups, $H(2) = 5.81$, $p = .05$. Despite the lack of statistical significance, the mean performance values suggest a trend where participants in the EMS group (M = 4.08, SD = 1.83) performed better on average than those in the Electrotactile (M = 3.27, SD = 1.15) and Control (M = 3.18, SD = 1.63) groups. The median values further support this trend, with EMS showing the highest median performance (3.61), followed by Electrotactile (3.20) and Control (2.85). The groups were ranked accordingly, with EMS achieving the highest rank, followed by Electrotactile and Control.

Post-Training 2. We conducted a Kruskal-Wallis test to evaluate the differences in Path Length in Post-Training 2. The results revealed a statistically significant difference between the groups,

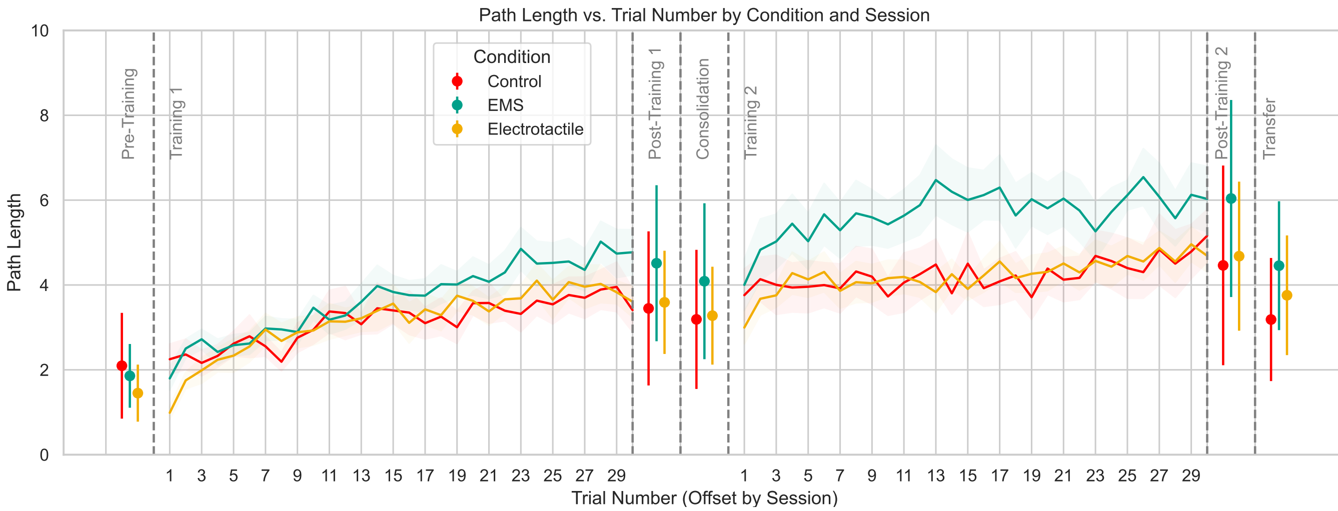

Figure 6: Path Length plots throughout the experiment, from the pre-training assessment to the transfer test. This figure offers a trial-by-trial overview, illustrating the progression of the participant's motor skills, as reflected by changes in Path Length over time. Shaded areas represent the standard error.

$H(2) = 11.911$, $p = .003$. Post-hoc pairwise comparisons using Dunn's test with Bonferroni correction indicated that the EMS group significantly outperformed the Control group ($p = 0.002$). At the same time, no significant differences were observed between the Electrotactile and Control groups ($p = .98$) or between the EMS and Electrotactile groups ($p = .05$). Based on mean performance values, the EMS condition ranked highest (M = 6.04, SD = 2.32), followed by the Electrotactile condition (M = 4.68, SD = 1.76), and finally the Control condition (M = 4.46, SD = 2.35). These findings suggest that the EMS feedback led to superior overall performance compared to the other feedback groups.

4.2 Total Time

We evaluated the Total Time across the three main assessments: *Post-Training 1*, *Consolidation*, and, *Post-training 2* across the three experimental conditions (Control, EMS, and Electrotactile). The results are as follows.

Post-Training 1. To investigate the differences in Total Time in Post-Training 1, we performed a Kruskal-Wallis test due to violating normality assumptions in at least one group. The Kruskal-Wallis test revealed a statistically significant difference between the groups, $H(2) = 9.15$, $p = .01$. We conducted Dunn's post-hoc test with Bonferroni correction to identify the specific group differences. The results showed a significant difference in Total Time between the Control and EMS groups ($p = .007$), while no significant differences were observed between the other pairwise comparisons (all $p > .05$).

The group performance ranking, based on mean values, indicated that the EMS condition had the lowest mean Total Time (M = 26.97, SD = 9.74, median = 27.27), followed by the Electrotactile condition (M = 31.70, SD = 12.48, median = 27.88), and the Control condition had the highest mean Total Time (mean = 34.43, SD = 11.39, median = 33.16). These results suggest that the EMS condition led to significantly faster completion times than the Control condition. In contrast, the Electrotactile condition did not differ significantly from either the Control or EMS conditions.

Consolidation. We evaluated the differences in Total Time in the Consolidation assessment using the Kruskal-Wallis test due to the non-normal distribution of the data. The test revealed a statistically significant difference between the groups, $H(2) = 6.79$, $p = .034$.

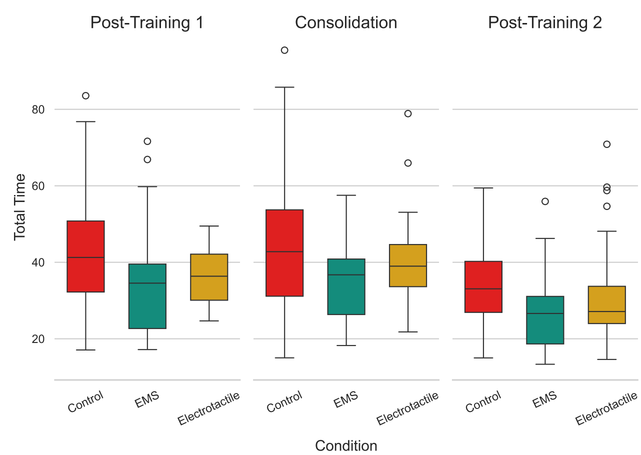

Figure 7: Total Time Across the Three Assessments. The boxplots show total time for the three main phases: Post-Training 1, Consolidation, and Post-Training 2, across Control, EMS, and Electrotactile conditions. The EMS and Electrotactile conditions consistently exhibited shorter total times, indicating better performance compared to the Control condition. Outliers are marked with circles.

Dunn's post-hoc test with Bonferroni correction was conducted to investigate these differences further. The results indicated a significant difference in Total Time between the Control and EMS groups (p = .02), while no significant differences were found between the other group pairs (all $p > .05$).

The mean Total Time for the EMS group was 35.86 seconds (SD = 10.68), followed by the Electrotactile group at 40.73 seconds (SD = 11.21), and the Control group at 45.89 seconds (SD = 18.07). Ranking the groups based on mean values, the EMS group performed the best, followed by the Electrotactile group and the Control group. These results suggest that the EMS condition led to a significantly lower Total Time compared to the Control condition in the consolidation test.

Post-Training 2. To examine the differences in *Total Time* in Post-Training 2, we performed a Kruskal-Wallis test due to the non-normal distribution of the data. The Kruskal-Wallis test revealed a statistically significant difference between the groups, $H(2) = 8.98$, $p = .01$. Post-hoc pairwise comparisons using Dunn's test with Bonferroni correction indicated that the EMS condition significantly differed from the Control condition (p = .008). At the same time, no significant differences were found between the other pairs (all $p > .05$).

Ranking the group performances based on mean *Total Time*, the EMS condition had the shortest mean time (M = 35.14, SD = 13.49), followed by the Electrotactile condition (M = 37.08, SD = 6.64), and the Control condition had the longest mean time (M = 44.22, SD = 15.81). These results suggest that EMS was the most efficient condition in terms of total time in Post-Training 2, while the Control condition required the most time on average.

4.3 Path Exits

We evaluated the Path Exits across the three main assessments: *Post-Training 1*, *Consolidation*, and, *Post-training 2* across the three experimental conditions (Control, EMS, and Electrotactile). The results are as follows.

Post-Training 1. To evaluate the differences in Path Exits in Post-Training 1, we conducted a Kruskal-Wallis test due to the non-normal distribution of the data. The test revealed a statistically significant difference between the groups, $H(2) = 10.33$, $p = .006$. Post-hoc pairwise comparisons using Dunn's test with Bonferroni correction indicated a significant difference between the Control group and the EMS group (p = .006). Although no significant differences were found between the other group pairs (all $p > 0.05$), the ranking of group performance based on mean values showed that the EMS condition (M = 2.42, SD = 2.36) had the highest number of path exits, followed by the Electrotactile condition (M = 2.03, SD = 2.56), and the Control condition (M = 1.14, SD = 2.27) had the lowest. These results suggest that the EMS condition led to a significantly higher number of path exits compared to the Control condition.

Consolidation. We conducted a Kruskal-Wallis test to evaluate the differences in Path Exits in the Consolidation, as the data did not meet the assumptions for parametric testing. The Kruskal-Wallis test revealed no statistically significant difference between the groups, $H(2) = 3.42$, $p = .18$.

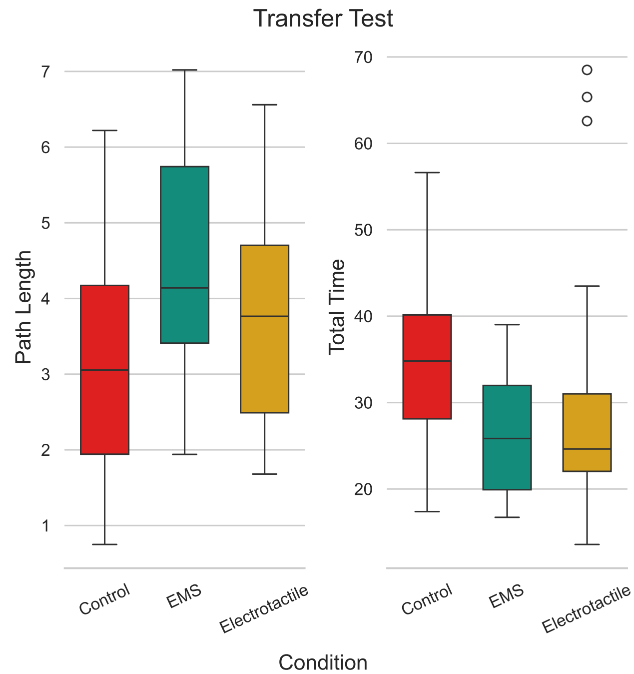

Figure 8: Performance Comparison During the Motor Transfer Test. The boxplots illustrate Path Length (left) and Total Time (right) across the three conditions: Control, EMS, and Electrotactile. The EMS condition demonstrates shorter path lengths and reduced total time, indicating superior performance compared to the Control and Electrotactile conditions. Outliers are marked with circles.

Post-Training 2. To analyze differences in the dependent variable *Path Exits* in the Post-Training 2, we conducted a Kruskal-Wallis test due to the non-normality of the data. The test revealed a statistically significant difference between the groups, $H(2) = 6.11$, $p = .04$. Post-hoc pairwise comparisons using Dunn's test with Bonferroni correction showed no significant pairwise differences between any two conditions (all $p > 0.05$).

4.4 Transfer Tests

We analyzed the Motor transfer with a different shape in the MD task at the end of the last training session. Here, we analyze the motor transfer performance across the main motor learning operationalization of the MD task: Path Length, Total Time, and Path Exits; the results are as follows.

Path Length. To assess the feedback impact on *Path Length* for motor transfer, we conducted a one-way ANOVA followed by Tukey's (HSD) post-hoc test. The ANOVA revealed a statistically significant effect of condition on *Path Length*, $F(2, n) = 6.81$, $p = .002$. Post-hoc comparisons using Tukey's HSD test showed that the mean difference between the Control and EMS groups was significant (MD = 1.26, p = .001), with the EMS group demonstrating a higher mean Path Length. However, no significant differences were found between the other group pairs (all $> p = 0.05$). The ranking of group performance based on mean values was as follows: EMS (M = 4.45, SD = 1.52), Electrotactile (M = 3.76, SD = 1.41), and Control (M = 3.19, SD = 1.45). These results suggest that the EMS condition led to a significantly higher *Path Length* compared to the Control condition.

Total Time. To evaluate the differences in Total Time in the motor transfer test, we conducted a Kruskal-Wallis test, as the assumption of normality was not met. The results indicated a statistically significant difference between the groups, $H(2) = 13.73$, $p = .001$. Post-hoc comparisons using Dunn's test with Bonferroni correction revealed significant differences between the Control group and both the EMS group ($p = .004$) and the Electrotactile group ($p = .004$), while no significant difference was found between the EMS and Electrotactile groups ($p > .05$).

The mean *Total Time* values for each group ranked the EMS condition as the fastest ($M = 26.88$, $SD = 6.92$), followed by the Electrotactile condition ($M = 28.73$, $SD = 12.86$), and the Control condition being the slowest ($M = 34.48$, $SD = 9.86$). These results suggest that both the EMS and Electrotactile conditions resulted in significantly faster task completion times compared to the Control condition, with the EMS condition being the most efficient overall.

Path Exits. To evaluate the differences in Path Exits in the motor transfer test, we conducted a Kruskal-Wallis test due to the non-normal distribution of the data. The Kruskal-Wallis test revealed a statistically significant difference between the groups, $H(2) = 9.06$, $p = .01$. Subsequent pairwise comparisons using Dunn's post-hoc test with Bonferroni correction indicated a significant difference between the Control and Electrotactile conditions ($p = .012$), while the comparisons between Control and EMS and between EMS and Electrotactile were not statistically significant.

Group performance rankings, based on the mean values of *Path Exits*, indicate that the Control group had the lowest mean (M = 1.06, SD = 1.82), followed by the EMS group (M = 2.03, SD = 2.01), and the Electrotactile group with the highest mean (M = 2.61, std = 2.72). These results suggest that participants in the Control condition experienced fewer path exits compared to those in the Electrotactile condition, with the EMS condition showing intermediate performance.

4.5 Learning Model Parameters

Using nonlinear least squares (NLS) regression, we fitted an exponential decay model to the response times across the three experimental conditions on a population level [23, 80]. We dynamically estimated starting values for the model parameters to improve the fitting process. We then extracted the coefficients (A, B, and α) from the fitted models. A visualization of the fitted models is shown in Figure 9, and the resulting parameters are presented in Table 1

Based on the extracted coefficients of the Exponential Decay model, the Control condition shows a higher asymptotic response time ($A = 33.019$) compared to EMS ($A = 24.802$) and Electrotactile ($A = 34.553$), indicating that participants in the EMS condition achieve the fastest minimum response time after practice. The EMS condition also demonstrates the most significant change in response time from the beginning to the end of practice ($B = 34.602$), suggesting an improvement in performance over time. Interestingly, the Electrotactile condition exhibits the highest learning rate ($\alpha = .094$), implying that participants in this group adapted more quickly during practice, even if their final time (as reflected in A) was not as short as in the EMS condition.

Table 1: Model Coefficients for the Exponential Decay Model. A represents the asymptotic response time, B reflects the performance improvement, and α denotes the learning rate. The EMS condition achieved the lowest final response time ($A = 24.802$) and largest improvement ($B = 34.602$), while the Electrotactile condition showed the highest learning rate ($\alpha = .094$).

Condition	A	B	α
Control	33.019	25.813	.046
EMS	24.802	34.602	.053
Electrotactile	34.553	29.297	.094

4.6 Task Load

To evaluate the differences in Task Load Across conditions, we conducted Kruskal-Wallis test across the six subscales of the NASA-TLX questionnaire, as the data did not meet the assumptions for parametric testing. The Kruskal-Wallis test revealed no statistically significant difference between the groups in any subscale (all $p > .05$). The individual subscale scores are depicted in Table 2.

4.7 Usability

To analyze differences in the System Usability Scale (SUS) scores across the three conditions a one-way ANOVA was conducted. The ANOVA revealed a statistically significant difference between the groups, $F(2, 36) = 3.976$, $p = .028$. Post-hoc analysis indicated a significant difference between the Control group and the Electrotactile group (MD = 14.90, $p = .023$), with the Electrotactile group demonstrating higher SUS scores. No significant differences were found between the other group pairs (all $p > .05$). We refer to Table 2 for the detailed SUS scores per condition.

5 Discussion

In this paper, we present an empirical evaluation of the effects of EMS on motor learning, comparing it to two other conditions: an Electrotactile feedback condition, representing the state-of-the-art feedback type, and a Control condition with no feedback intervention as a baseline. Our study examined motor learning across three key phases: fast learning, consolidation, and motor transfer. We aimed to explore the tension between recent HCI research, which suggests that EMS can enhance motor learning, and traditional motor learning theories that emphasize the importance of repeated practice for the creation of sensorimotor representations through perception, reflection, and correction of motor actions. Our findings reveal that the EMS group outperformed both the Electrotactile and Control groups across all phases of motor learning, with the Electrotactile condition yielding intermediate results. However, there are important considerations when selecting

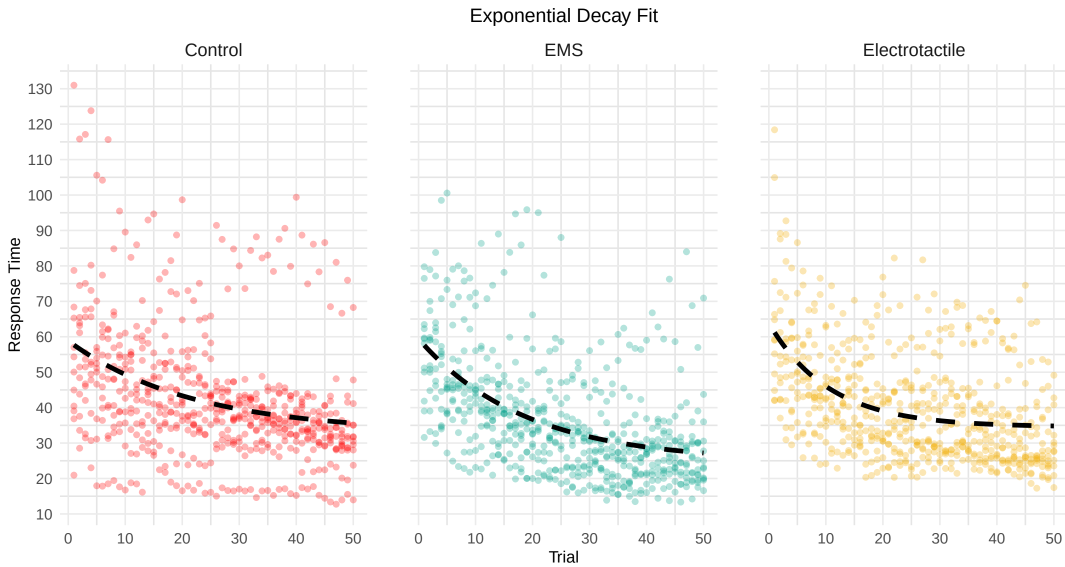

Figure 9: Exponential decay model fitted to the data for the experimental groups. The lines represent the model's predicted values, while the scatter points indicate the actual TOTAL TIME data recorded for each trial under each condition. The TOTAL TIME to complete the shapes was used as the Response Time variable in this analysis.

Table 2: Descriptive Statistics for NASA-TLX Subscales and System Usability Scale (SUS). The table presents mean values for the six NASA-TLX dimensions (Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration) and the SUS scores across three experimental conditions: Control, EMS, and Electrotactile. Standard deviations are provided in parentheses. Lower scores for NASA-TLX dimensions indicate lower workload, while higher SUS scores reflect better perceived usability.

Condition	Mental (SD)	Physical (SD)	Temporal (SD)	Performance (SD)	Effort (SD)	Frustration (SD)	SUS (SD)
Control	12.77 (3.56)	12.77 (4.62)	9.92 (3.73)	11.08 (4.31)	12.31 (2.87)	10.92 (4.54)	56.35 (15.13)
EMS	13.85 (3.60)	11.23 (5.02)	9.15 (2.82)	12.00 (2.86)	13.00 (3.70)	8.38 (4.35)	65.77 (13.48)
Electrotactile	11.83 (5.06)	8.42 (5.47)	7.17 (2.82)	13.17 (2.92)	15.00 (2.49)	7.75 (5.82)	71.25 (11.15)

feedback mechanisms for motor tasks, which we discuss in detail in this section:

5.1 EMS as Augmentation Technology for Motor Skills

Previous research has consistently shown the efficacy of EMS in temporarily enhancing motor skills, such as reaction time and posture correction. While EMS has been associated with improved motor skill transfer, questions remain as to whether these improvements reflect genuine learning or are merely temporary augmentations dependent on active stimulation. In this paper, we present empirical evidence confirming that EMS-supported motor learning can result in lasting skill acquisition, extending beyond temporary performance gains. Our results demonstrate that EMS outperforms electrotactile (non-movement inducing) haptic feedback during sessions, corroborating the immediate augmentation potential reported by Kasahara et al. [26] and Tatsuno et al. [75]. However, we show that EMS not only enhances immediate performance but also promotes motor skill learning, suggesting a deeper connection between augmentation and learning than we previously assumed. *In this sense, **H1** could be rejected, as during the motor learning task, EMS showed better results than ELECTROTACTILE and CONTROL.*

5.2 Typical Feedback Modalities Remain Useful for Motor Learning

Our experimental results show that while ELECTROTACTILE feedback led to lower performance in some assessments, it significantly outperformed the CONTROL condition, making it a viable alternative for learning. According to the exponential decay model, ELECTROTACTILE feedback yielded a higher learning rate than EMS, reaching stable performance faster, though less intensively than EMS. Despite this, ELECTROTACTILE feedback demonstrated its effectiveness. Additionally, it offers practical advantages: it is easier to implement, requires less exhaustive calibration, and is more suitable for a wider range of users, as EMS can cause discomfort for some and targeting specific muscles can be challenging. Thus, ELECTROTACTILE feedback is not necessarily inferior to EMS but may be better suited for different scenarios depending on user goals. *However, we reject **H2**, as ELECTROTACTILE feedback did not result in better motor skill consolidation than EMS. Nonetheless, the results support **H3**, as ELECTROTACTILE feedback led to a higher learning rate than EMS.*

5.3 EMS for Motor Learning: Does EMS Support the Learning Process?

Our results provide empirical evidence that EMS not only enhances motor skills during use but also facilitates motor learning, viewed as the sustained improvement of a skill even after the removal of the EMS device—both immediately following training and after a delay of one or more days. Furthermore, the findings demonstrate that ELECTROTACTILE feedback also supports motor learning, consistent with prior research suggesting similar feedback mechanisms can promote learning. Contrary to our initial hypotheses, which were informed by the literature, EMS in this experiment led to greater overall motor learning compared to the CONTROL condition across various assessments and metrics, although the rate of learning was lower than that observed with ELECTROTACTILE feedback alone. *In consequence, given that EMS led to a higher overall learning, we reject **H4**.*

5.3.1 EMS and Electrotactile Feedback for Motor Transfer. Similarly, the effects of EMS extended to new motor tasks, indicating that the learning was not confined to the original motor skill but had been sufficiently internalized to transfer across different contexts. ELECTROTACTILE feedback demonstrated comparable performance under the conditions reported in this experiment. *Given this evidence, **H5** does not hold, as, contrary to our initial hypothesis, EMS did not lower the performance but instead resulted in a higher performance than the other two conditions.*

5.4 Potential Neurophysiological Mechanisms of EMS for Supporting Motor Learning

Learning models emphasize the importance of awareness during training to enhance the effectiveness of trial and error. Faltaous et al. [15] report that EMS first induces action, followed by perception and reflection, which could influence the learning process. However, as our results demonstrate, this did not hinder learning; in fact, EMS outperformed other conditions. We attribute this to the alignment of participant intention with EMS actuation throughout the experiment. Specifically, participants aimed to correct their path, and EMS facilitated this by actuating the wrist, potentially contributing to a heightened sense of agency. Kasahara et al. [27] similarly found that participants exhibited increased reaction times after EMS actuation, but only when agency was sufficiently present, whereas conditions with no actuation or agency did not show this effect. Our findings suggest that, beyond the action-perception-reflection sequence, the sense of agency—particularly how participant intention aligns with EMS stimulation—plays a critical role in the learning process. Therefore, future research should explore how varying levels of agency affect motor skill training with EMS support.

Another possible explanation for this effect is that, contrary to the sequential model proposed by Faltaous et al. [15], action and perception may occur simultaneously. In this case, users might be learning while EMS is stimulating their body, in addition to subsequent reflection. Supporting this, Hagert et al. [20] demonstrate that EMS stimulation on the wrist triggers a proprioceptive response, which could provide supplementary feedback alongside kinaesthetic information.

5.5 Implications for Motor Learning in HCI using EMS

Despite previous claims regarding the potential of EMS in supporting motor learning, concrete empirical evidence has been lacking. Prior research primarily focused on short-term effects, often limited to a single session, leaving the broader impact of EMS on long-term motor learning unclear. Moreover, the distinction between EMS merely augmenting motor performance and genuinely supporting motor learning has not been fully established.

Our findings provide empirical evidence that EMS not only enhances immediate motor performance but also contributes to long-term motor learning. However, our results indicate that traditional feedback mechanisms [72]—which provide users with additional information and allow them to make their own corrections—still lead to higher learning rates. Thus, while EMS is effective, it may not entirely replace more conventional feedback approaches for motor learning, especially when it comes to fostering independent error correction and self-guided improvement.

Nevertheless, EMS shows significant promise in reducing the learning ceiling often observed with traditional [72] feedback methods. By offering direct physical guidance, EMS can speed up the learning process, especially for tasks where users struggle to make appropriate corrections independently. Future research should explore the potential of EMS to complement, rather than replace, traditional feedback systems in motor learning tasks, particularly for users with different learning capabilities.

5.6 Real-World Implications

The findings of this work apply to motor learning using EMS at an abstract level and have practical implications in real-world scenarios. Below, we provide a non-exhaustive list of examples: Faltaous et al. [16] explored various situations where EMS can be beneficial. Our work aligns with their findings on action manipulation, skill acquisition in sports, musical instrument training, specifically percussion training, and learning new gestures. Similarly, Shahu et al. [67] conducted a scenario-based investigation, where our results are particularly relevant to motor learning contexts such as guitar training. Furthermore, in the taxonomy proposed by Faltaous et al. [15], our findings have implications for scenarios categorized under action and augmentation. This intersection includes applications such as teaching musical instruments, facilitating sports training (e.g., running, bowling, and golf), guiding orientation in 3D space, and VR-based skill learning. In detail, this manuscript provides empirical support that these scenarios can improve motor skill learning through EMS. Still, users can also perform better (i.e., be augmented) by using EMS during the training.

5.7 Recommended Practices for EMS in Motor Learning and Augmentation

Based on the result presented in this manuscript, and previous works the following best practices are recommended to ensure the validity and reliability of results when using EMS in motor learning or augmentation studies:

- **Differentiate Learning vs. Augmentation:** Clearly distinguish between experiments aimed at enhancing motor learning and those focused on augmenting motor performance. Learning should be assessed over time, whereas augmentation effects can be measured immediately after, or during EMS intervention.
- **Allow Time for Learning:** When testing for learning outcomes, provide adequate time for participants to consolidate motor skills, either during or after the session. For motor learning studies, schedule sessions with sufficient time in between, ideally with a sleep interval, as this supports skill consolidation [39]. To accurately assess motor learning, design studies ideally would involve at least two sessions, separated by a period of sleep. This helps isolate the long-term effects of EMS on learning from short-term performance enhancements.
- **Ensure Agency:** Guarantee a sufficient sense of agency during EMS interventions. Participants should feel that their intentions and actions are aligned with EMS stimulation, as agency is a crucial factor in effective motor learning and performance augmentation.
- **Skill Assessment Before Intervention:** Assess participants' baseline motor skills before introducing EMS. This will provide a clearer understanding of the effects of EMS on motor learning or augmentation and allow for a more personalized approach to EMS intensity and feedback.
- **Avoid Repeated Measures for Learning Assessments, Introduce rest intervals for Augmentation Assessments:** When testing motor learning, avoid using repeated measures designs that could confound results with practice effects. If augmentation is being assessed, introduce a rest interval between blocks to account for the immediate effects of EMS, as demonstrated in the findings of Kasahara et al. [27]

5.8 Limitations

While this work aims to comprehensively address the effects of EMS feedback on motor learning, several limitations of the current setup must be acknowledged. First, although we cover multiple phases of motor learning, we do not extend to the most advanced phases, such as automatic execution. This would require a significantly higher number of sessions, which, given the three conditions and participant numbers, would be resource-intensive. However, these post-consolidation stages are equally important for the motor learning process, particularly for participants aiming to achieve high levels of skill in a given task. Additionally, our measurements were limited to behavioral responses, lacking physiological data such as EEG or fMRI that could provide further insights into the mechanisms of EMS in motor learning. Also, although we studied motor learning in multiple stages and sessions, the timeframe studied in the current manuscript might be insufficient to provide definitive insights about the long-term effects of EMS on motor learning; future works should consider longitudinal studies to address this. Finally, we did not evaluate participants' sense of agency, which could offer valuable information about the impact of agency levels on learning effectiveness.

5.9 Next Steps in Motor Learning using EMS

In advancing our understanding of motor learning with EMS, several avenues for future work are identified; **Exploring the underlying mechanisms of EMS in motor learning:** While the current research demonstrates the potential of EMS in enhancing motor learning, a deeper investigation into its physiological mechanisms is necessary. Utilizing tools like EEG or fMRI could provide valuable insights into how EMS influences neural pathways and motor control systems during learning. **Determining the ceiling effect of EMS in motor learning:** It remains unclear whether there is a point at which EMS reaches a threshold of effectiveness in motor learning. Future studies should aim to identify whether there is a diminishing return in skill acquisition with prolonged EMS exposure or if it continues to offer incremental benefits over time/sessions. And, finally **Agency as a critical factor:** Preserving a sense of agency remains a key consideration in EMS-based interventions, as highlighted by Kasahara et al. [27]. Understanding how different levels of agency affect motor learning outcomes will be crucial in designing more effective EMS applications, and a logical next step in light of the results presented in this paper.

6 Conclusion

We investigated the impact of EMS on motor learning compared to electrotactile feedback and a control condition. Our results showed that EMS outperformed both electrotactile feedback and the control condition across all assessments, including within-session (fast-learning), across-session (consolidation), and learning transfer evaluations. Consistent with motor learning models, electrotactile feedback resulted in the highest learning rate. However, EMS also demonstrated a higher learning rate than the control condition, indicating that it does not disrupt the sensorimotor representation of the task. Overall, EMS led to a greater gain in learning compared to the other two conditions. These findings offer empirical support for the effectiveness of EMS in motor learning, reinforcing claims in HCI literature regarding its potential in this domain.

Acknowledgments

This work is supported by the German Research Foundation (DFG), CRC 1404: "FONDA: Foundations of Workflows for Large-Scale Scientific Data Analysis" (Project-ID 414984028). Aalto Science Institute funded Steeven Villa. This work was supported by the national infrastructure for human virtualization and remote presence, MAGICS.

References

[1] Zainab Alrubaye, Moaaz Hudhud Mughrabi, Banu Manav, and Anil Ufuk Batmaz. 2024. Effects of color cues on eye-hand coordination training with a mirror drawing task in virtual environment. *Frontiers in Psychology* 14 (Jan. 2024). https://doi.org/10.3389/fpsyg.2023.1307590 Publisher: Frontiers.

[2] Kamal Narayan Arya, Shanta Pandian, Dharmendra Kumar, and Vinod Puri. 2015. Task-Based Mirror Therapy Augmenting Motor Recovery in Poststroke Hemiparesis: A Randomized Controlled Trial. *Journal of Stroke and Cerebrovascular Diseases* 24, 8 (Aug. 2015), 1738–1748. https://doi.org/10.1016/j.jstrokecerebrovasdis.2015.03.026

[3] Jonas Auda, Max Pascher, and Stefan Schneegass. 2019. Around the (Virtual) World: Infinite Walking in Virtual Reality Using Electrical Muscle Stimulation. In

Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems. ACM, Glasgow Scotland Uk, 1–8. https://doi.org/10.1145/3290605.3300661

[4] Braj Bhushan, C. B. Dwivedi, R. Mishra, and Manas K. Mandal. 2000. Performance on a Mirror-Drawing Task by Non-Right-Handers. *The Journal of General Psychology* 127, 3 (July 2000), 271–277. https://doi.org/10.1080/00221300009598585 Publisher: Routledge _eprint: https://doi.org/10.1080/00221300009598585.

[5] Aneta Demidas. 2021. Electrical stimulation: then and now. Applications and limitations. *Physiotherapy Quarterly* 29, 4 (2021), 81–86. https://doi.org/10.5114/pq.2021.110987

[6] Lise Desmottes, Christelle Maillart, and Thierry Meulemans. 2017. Mirror-drawing skill in children with specific language impairment: Improving generalization by incorporating variability into the practice session. *Child Neuropsychology* 23, 4 (May 2017), 463–482. https://doi.org/10.1080/09297049.2016.1170797 Publisher: Routledge _eprint: https://doi.org/10.1080/09297049.2016.1170797.

[7] Krishnagopal Dharani. 2015. Chapter 3 - Memory. In *The biology of thought: A neuronal mechanism in the generation of thought-A new molecular model*, Krishnagopal Dharani (Ed.). Academic Press, San Diego, 53–74. https://doi.org/10.1016/B978-0-12-800900-0.00003-8

[8] Jörn Diedrichsen, Olivier White, Darren Newman, and Níall Lally. 2010. Use-Dependent and Error-Based Learning of Motor Behaviors. *Journal of Neuroscience* 30, 15 (April 2010), 5159–5166. https://doi.org/10.1523/JNEUROSCI.5406-09.2010 Publisher: Society for Neuroscience Section: Articles.

[9] Paul Dourish. 2001. *Where the action is: the foundations of embodied interaction*. MIT Press, Cambridge, MA, USA.

[10] Julien Doyon, Pierre Bellec, Rhonda Amsel, Virginia Penhune, Oury Monchi, Julie Carrier, Stéphane Lehéricy, and Habib Benali. 2009. Contributions of the basal ganglia and functionally related brain structures to motor learning. *Behavioural Brain Research* 199, 1 (April 2009), 61–75. https://doi.org/10.1016/j.bbr.2008.11.012

[11] Ayaka Ebisu, Satoshi Hashizume, and Yoichi Ochiai. 2018. Building a Feedback Loop between Electrical Stimulation and Percussion Learning. In *ACM SIGGRAPH 2018 Studio (SIGGRAPH '18)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3214822.3214824 event-place: Vancouver, British Columbia, Canada.

[12] Ayaka Ebisu, Satoshi Hashizume, Kenta Suzuki, Akira Ishii, Mose Sakashita, and Yoichi Ochiai. 2017. Stimulated percussions: method to control human for learning music by using electrical muscle stimulation. In *Proceedings of the 8th Augmented Human International Conference*. ACM, Silicon Valley California USA, 1–5. https://doi.org/10.1145/3041164.3041202

[13] Sarah Faltaous, Aya Abdulmaksoud, Markus Kempe, Florian Alt, and Stefan Schneegass. 2021. GeniePutt: Augmenting human motor skills through electrical muscle stimulation. *it - Information Technology* 63, 3 (July 2021), 157–166. https://doi.org/10.1515/itit-2020-0035 Publisher: De Gruyter Oldenbourg.

[14] Sarah Faltaous, Anna Hubert, Jakob Karolus, Steeven Villa, Thomas Kosch, and Pawel W. Wozniak. 2022. EMStriker: Potentials of Enhancing the Training Process of Racket-based Sports via Electrical Muscle Stimulation. In *Proceedings of the Sixteenth International Conference on Tangible, Embedded, and Embodied Interaction (TEI '22)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3490149.3505578

[15] Sarah Faltaous, Marion Koelle, and Stefan Schneegass. 2022. From Perception to Action: A Review and Taxonomy on Electrical Muscle Stimulation in HCI. In *Proceedings of the 21st International Conference on Mobile and Ubiquitous Multimedia*. ACM, Lisbon Portugal, 159–171. https://doi.org/10.1145/3568444.3568460

[16] Sarah Faltaous, Julie R. Williamson, Marion Koelle, Max Pfeiffer, Jonas Keppel, and Stefan Schneegass. 2024. Understanding User Acceptance of Electrical Muscle Stimulation in Human-Computer Interaction. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 428, 16 pages. https://doi.org/10.1145/3613904.3642585

[17] Paul M Fitts and Michael I Posner. 1967. Human performance. (1967).

[18] J. Randall Flanagan, Philipp Vetter, Roland S. Johansson, and Daniel M. Wolpert. 2003. Prediction Precedes Control in Motor Learning. *Current Biology* 13, 2 (Jan. 2003), 146–150. https://doi.org/10.1016/S0960-9822(03)00007-1 Publisher: Elsevier.

[19] L.A. Geddes. 1994. The first stimulators-reviewing the history of electrical stimulation and the devices crucial to its development. *IEEE Engineering in Medicine and Biology Magazine* 13, 4 (1994), 532–542. https://doi.org/10.1109/51.310995

[20] Elisabet Hagert, Jonas K. E. Persson, Michael Werner, and Björn-Ove Ljung. 2009. Evidence of Wrist Proprioceptive Reflexes Elicited After Stimulation of the Scapholunate Interosseous Ligament. *The Journal of Hand Surgery* 34, 4 (April 2009), 642–651. https://doi.org/10.1016/j.jhsa.2008.12.001

[21] Sandra G. Hart and Lowell E. Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In *Human Mental Workload*, Peter A. Hancock and Najmedin Meshkati (Eds.). Advances in Psychology, Vol. 52. North-Holland, 139–183. https://doi.org/10.1016/S0166-4115(08)62386-9

[22] Mahmoud Hassan, Florian Daiber, Frederik Wiehr, Felix Kosmalla, and Antonio Krüger. 2017. FootStriker: An EMS-based Foot Strike Assistant for Running. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 1, 1 (March 2017), 2:1–2:18. https://doi.org/10.1145/3053332

[23] Andrew Heathcote, Scott Brown, and D. J. K. Mewhort. 2000. The power law repealed: The case for an exponential law of practice. *Psychonomic Bulletin & Review* 7, 2 (June 2000), 185–207. https://doi.org/10.3758/BF03212979

[24] Md Shafiqul Islam and Sol Lim. 2022. Vibrotactile feedback in virtual motor learning: A systematic review. *Applied Ergonomics* 101 (May 2022), 103694. https://doi.org/10.1016/j.apergo.2022.103694

[25] Mona Sharon Julius and Esther Adi-Japha. 2016. A Developmental Perspective in Learning the Mirror-Drawing Task. *Frontiers in Human Neuroscience* 10 (March 2016), 83. https://doi.org/10.3389/fnhum.2016.00083

[26] Shunichi Kasahara, Jun Nishida, and Pedro Lopes. 2019. Preemptive Action: Accelerating Human Reaction Using Electrical Muscle Stimulation Without Compromising Agency. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3290605.3300873 event-place: Glasgow, Scotland Uk.

[27] Shunichi Kasahara, Kazuma Takada, Jun Nishida, Kazuhisa Shibata, Shinsuke Shimojo, and Pedro Lopes. 2021. Preserving Agency During Electrical Muscle Stimulation Training Speeds up Reaction Time Directly After Removing EMS. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. ACM, Yokohama Japan, 1–9. https://doi.org/10.1145/3411764.3445147

[28] Adam W Kiefer, J Gualberto Cremades, and Gregory D Myer. 2014. Train the Brain: Novel Electroencephalography Data Indicate Links between Motor Learning and Brain Adaptations. *Journal of novel physiotherapies* 4, 2 (April 2014), 198. https://doi.org/10.4172/2165-7025.1000198

[29] Dongwon Kim, Brandon J. Johnson, R. Brent Gillespie, and Rachael D. Seidler. 2014. The effect of haptic cues on motor and perceptual based implicit sequence learning. *Frontiers in Human Neuroscience* 8 (March 2014), 130. https://doi.org/10.3389/fnhum.2014.00130

[30] Sungshin Kim, Kenji Ogawa, Jinchi Lv, Nicolas Schweighofer, and Hiroshi Imamizu. 2015. Neural substrates related to motor memory with multiple timescales in sensorimotor adaptation. *PLoS biology* 13, 12 (2015), e1002312.

[31] J. Knibbe, A. Alsmith, and K. Hornbæk. 2018. Experiencing Electrical Muscle Stimulation. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2, 3, Article 118 (sep 2018), 14 pages. https://doi.org/10.1145/3264928

[32] Robert Laforce and Julien Doyon. 2002. Differential role for the striatum and cerebellum in response to novel movements using a motor learning paradigm. *Neuropsychologia* 40, 5 (Jan. 2002), 512–517. https://doi.org/10.1016/S0028-3932(01)00128-2

[33] Guilherme M. Lage, Herbert Ugrinowitsch, Tércio Apolinário-Souza, Márcio Mário Vieira, Maicon R. Albuquerque, and Rodolfo Novellino Benda. 2015. Repetition and variation in motor practice: A review of neural correlates. *Neuroscience & Biobehavioral Reviews* 57 (Oct. 2015), 132–141. https://doi.org/10.1016/j.neubiorev.2015.08.012

[34] James R. Lewis. 2018. The System Usability Scale: Past, Present, and Future. *International Journal of Human–Computer Interaction* 34, 7 (July 2018), 577–590. https://doi.org/10.1080/10447318.2018.1455307 Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/10447318.2018.1455307.

[35] Zong-Ming Li, Laurel Kuxhaus, Jesse A. Fisk, and Thomas H. Christophel. 2005. Coupling between wrist flexion–extension and radial–ulnar deviation. *Clinical Biomechanics* 20, 2 (Feb. 2005), 177–183. https://doi.org/10.1016/j.clinbiomech.2004.10.002

[36] Pedro Lopes, Doăa Yüksel, François Guimbretière, and Patrick Baudisch. 2016. Muscle-plotter: An Interactive System based on Electrical Muscle Stimulation that Produces Spatial Output. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*. ACM, Tokyo Japan, 207–217. https://doi.org/10.1145/2984511.2984530

[37] Andreas R Luft and Manuel M Buitrago. 2005. Stages of motor skill learning. *Molecular neurobiology* 32, 3 (2005), 205–216. https://doi.org/10.1385/MN:32:3:205

[38] Zandor Machaen, Luis Martin, and Jonathan-Hernando Rosales. 2021. Bio-inspired cognitive model of motor learning by imitation. *Cognitive Systems Research* 66 (2021), 134–149.

[39] Pierre Maquet. 2001. The role of sleep in learning and memory. *science* 294, 5544 (2001), 1048–1052. https://doi.org/10.1126/science.1062856

[40] Ray Marks. 1996. Ipsilateral and Contralateral Skill Acquisition following Random Practice of Unilateral Mirror-Drawing. *Perceptual and Motor Skills* 83, 3 (Dec. 1996), 715–722. https://doi.org/10.2466/pms.1996.83.3.715 Publisher: SAGE Publications Inc.

[41] Hiroaki Masaki and Werner Sommer. 2012. Cognitive neuroscience of motor learning and motor control. *The Journal of Physical Fitness and Sports Medicine* 1, 3 (2012), 369–380. https://doi.org/10.7600/jpfsm.1.369

[42] Raymond W. McGorry, Chien-Chi Chang, and Patrick G. Dempsey. 2004. A technique for estimation of wrist angular displacement in radial/ulnar deviation and flexion/extension. *International Journal of Industrial Ergonomics* 34, 1 (July 2004), 21–29. https://doi.org/10.1016/j.ergon.2004.01.005

[43] R. C. Miall and J. Cole. 2007. Evidence for stronger visuo-motor than visuo-proprioceptive conflict during mirror drawing performed by a deafferented subject and control subjects. *Experimental Brain Research* 176, 3 (Jan. 2007), 432–439. https://doi.org/10.1007/s00221-006-0626-0

[44] Darryl Millis and David Levine. 2013. *Canine Rehabilitation and Physical Therapy*. Elsevier Health Sciences. Google-Books-ID: nSxEAwAAQBAJ.

[45] J. Moreno-Aranda and A. Seireg. 1981. Electrical parameters for over-the-skin muscle stimulation. *Journal of Biomechanics* 14, 9 (1981), 579–585. https://doi.org/10.1016/0021-9290(81)90083-X

[46] A. Newell and Paul Rosenbloom. 1993. Mechanisms of skill acquisition and the law of practice. *Cognitive Skills and Their Acquisition* Vol. 1 (Aug. 1993).

[47] Arinobu Niijima. 2023. Learning Effects and Retention of Electrical Muscle Stimulation in Piano Playing. In *Proceedings of the 2023 ACM International Symposium on Wearable Computers (ISWC '23)*. Association for Computing Machinery, New York, NY, USA, 104–108. https://doi.org/10.1145/3594738.3611373

[48] Arinobu Niijima, Toki Takeda, Ryosuke Aoki, and Shinji Miyahara. 2022. Muscle Synergies Learning with Electrical Muscle Stimulation for Playing the Piano. In *Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (UIST '22)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/3526113.3545666

[49] Arinobu Niijima, Toki Takeda, Kentaro Tanaka, Ryosuke Aoki, and Yukio Koike. 2021. Reducing Muscle Activity when Playing Tremolo by Using Electrical Muscle Stimulation to Learn Efficient Motor Skills. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 5, 3 (Sept. 2021), 123:1–123:17. https://doi.org/10.1145/3478110

[50] Jun Nishida, Shunichi Kasahara, and Kenji Suzuki. 2017. Wired Muscle: Generating Faster Kinesthetic Reaction by Inter-Personally Connecting Muscles. In *ACM SIGGRAPH 2017 Emerging Technologies (SIGGRAPH '17)*. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3084822.3084844 event-place: Los Angeles, California.

[51] Yoshiki Nishikawa, Yui Atarashi, Shogo Sekiguchi, and Buntarou Shizuki. 2024. Effects of Electrical Muscle Stimulation on Memorability of Hand Gestures: A Preliminary Study. In *Universal Access in Human-Computer Interaction*, Margherita Antona and Constantine Stephanidis (Eds.). Springer Nature Switzerland, Cham, 88–105. https://doi.org/10.1007/978-3-031-60875-9_7

[52] Romain Nith, Shan-Yuan Teng, Pengyu Li, Yujie Tao, and Pedro Lopes. 2021. DextrEMS: Increasing Dexterity in Electrical Muscle Stimulation by Combining it with Brakes. In *The 34th Annual ACM Symposium on User Interface Software and Technology* (Virtual Event, USA) *(UIST '21)*. Association for Computing Machinery, New York, NY, USA, 414–430. https://doi.org/10.1145/3472749.3474759

[53] Selina M. Parry, Sue Berney, Catherine L. Granger, Renè Koopman, Doa El-Ansary, and Linda Denehy. 2013. Electrical Muscle Stimulation in the Intensive Care Setting: A Systematic Review*. *Critical Care Medicine* 41, 10 (Oct. 2013), 2406. https://doi.org/10.1097/CCM.0b013e3182923642

[54] Selina M Parry, Sue Berney, Catherine L Granger, Renè Koopman, Doa El-Ansary, and Linda Denehy. 2013. Electrical muscle stimulation in the intensive care setting: a systematic review. *Critical care medicine* 41, 10 (2013), 2406–2418. https://doi.org/10.1097/CCM.0b013e3182923642

[55] Rakesh Patibanda, Xiang Li, Yuzheng Chen, Aryan Saini, Christian N Hill, Elise van den Hoven, and Florian Floyd Mueller. 2021. Actuating Myself: Designing Hand-Games Incorporating Electrical Muscle Stimulation. In *Extended Abstracts of the 2021 Annual Symposium on Computer-Human Interaction in Play (CHI PLAY '21)*. Association for Computing Machinery, New York, NY, USA, 228–235. https://doi.org/10.1145/3450337.3483464

[56] Rakesh Patibanda, Nathalie Overdevest, Shreyas Nisal, Aryan Saini, Don Samitha Elvitigala, Jarrod Knibbe, Elise Van Den Hoven, and Florian 'Floyd' Mueller. 2024. Shared Bodily Fusion: Leveraging Inter-Body Electrical Muscle Stimulation for Social Play. In *Proceedings of the 2024 ACM Designing Interactive Systems Conference (DIS '24)*. Association for Computing Machinery, New York, NY, USA, 2088–2106. https://doi.org/10.1145/3643834.3660723

[57] Rakesh Patibanda, Nathalie Overdevest, Aryan Saini, Zhuying Li, Josh Andres, Jarrod Knibbe, Elise van den Hoven, and Florian 'Floyd' Mueller. 2024. Exploring Shared Bodily Control: Designing Augmented Human Systems for Intra- and Inter-Corporeality. In *Proceedings of the Augmented Humans International Conference 2024 (AHs '24)*. Association for Computing Machinery, New York, NY, USA, 318–323. https://doi.org/10.1145/3652920.3653037

[58] Max Pfeiffer, Tim Duente, and Michael Rohs. 2016. Let Your Body Move: A Prototyping Toolkit for Wearable Force Feedback with Electrical Muscle Stimulation. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '16)*. Association for Computing Machinery, New York, NY, USA, 418–427. https://doi.org/10.1145/2935334.2935348 event-place: Florence, Italy.

[59] Max Pfeiffer, Tim Dünte, Stefan Schneegass, Florian Alt, and Michael Rohs. 2015. Cruise Control for Pedestrians: Controlling Walking Direction using Electrical Muscle Stimulation. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. ACM, Seoul Republic of Korea, 2505–2514. https://doi.org/10.1145/2702123.2702190

[60] John P Porcari, Karen Palmer McLean, Carl Foster, Thomas Kernozek, Ben Crenshaw, and Chad Swenson. 2002. Effects of electrical muscle stimulation on body composition, muscle strength, and physical appearance. *The Journal of Strength & Conditioning Research* 16, 2 (2002), 165–172.

[61] Luc Proteau, Ronald G. Marteniuk, and Line Lévesque. 1992. A Sensorimotor Basis for Motor Learning: Evidence Indicating Specificity of Practice. *The Quarterly Journal of Experimental Psychology Section A* 44, 3 (April 1992), 557–575. https://doi.org/10.1080/14640749208401298 Publisher: Routledge _eprint: https://doi.org/10.1080/14640749208401298.

[62] Isabelle Rouleau, David P. Salmon, and Mirna Vrbancic. 2002. Learning, Retention and Generalization of a Mirror Tracing Skill in Alzheimer's Disease. *Journal of Clinical and Experimental Neuropsychology* 24, 2 (April 2002), 239–250. https://doi.org/10.1076/jcen.24.2.239.997 Publisher: Routledge _eprint: https://doi.org/10.1076/jcen.24.2.239.997.

[63] Jennifer E. Ruttle, Bernard Marius 't Hart, and Denise Y. P. Henriques. 2021. Implicit motor learning within three trials. *Scientific Reports* 11, 1 (Jan. 2021), 1627. https://doi.org/10.1038/s41598-021-81031-y Publisher: Nature Publishing Group.

[64] Richard A Schmidt and Craig A Wrisberg. 2008. *Motor learning and performance: A situation-based learning approach*. Human kinetics.

[65] Rachael D. Seidler. 2004. Multiple Motor Learning Experiences Enhance Motor Adaptability. *Journal of Cognitive Neuroscience* 16, 1 (Jan. 2004), 65–73. https://doi.org/10.1162/089892904322755566

[66] Deborah J. Serrien. 2009. Bimanual information processing and the impact of conflict during mirror drawing. *Behavioural Brain Research* 205, 2 (Dec. 2009), 391–395. https://doi.org/10.1016/j.bbr.2009.07.015

[67] Ambika Shahu, Philipp Wintersberger, and Florian Michahelles. 2022. Would Users Accept Electric Muscle Stimulation Controlling their Body? Insights from a Scenario-based Investigation. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems (CHI EA '22)*. Association for Computing Machinery, New York, NY, USA, 1–7. https://doi.org/10.1145/3491101.3519693

[68] Roland Sigrist, Georg Rauter, Robert Riener, and Peter Wolf. 2013. Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychonomic bulletin & review* 20, 1 (2013), 21–53. https://doi.org/10.3758/s13423-012-0333-8

[69] G. S. Snoddy. 1926. Learning and stability: a psychophysiological analysis of a case of motor learning with clinical applications. *Journal of Applied Psychology* 10, 1 (1926), 1–36. https://doi.org/10.1037/h0075814 Place: US Publisher: American Psychological Association.

[70] Daniel Starch. 1910. A demonstration of the trial and error method of learning. *Psychological Bulletin* 7, 1 (1910), 20–23. https://doi.org/10.1037/h0063796 Place: US Publisher: The Review Publishing Company.

[71] Shannon M. Stratton, Yeou-Teh Liu, Siang Lee Hong, Gottfried Mayer-Kress, and Karl M. Newell. 2007. Snoddy (1926) Revisited: Time Scales of Motor Learning. *Journal of Motor Behavior* 39, 6 (Nov. 2007), 503–515. https://doi.org/10.3200/JMBR.39.6.503-516 Publisher: Routledge _eprint: https://doi.org/10.3200/JMBR.39.6.503-516.

[72] Jennifer L. Sullivan, Shivam Pandey, Michael D. Byrne, and Marcia K. O'Malley. 2022. Haptic Feedback Based on Movement Smoothness Improves Performance in a Perceptual-Motor Task. *IEEE Transactions on Haptics* 15, 2 (April 2022), 382–391. https://doi.org/10.1109/TOH.2021.3126017

[73] Akifumi Takahashi, Jas Brooks, Hiroyuki Kajimoto, and Pedro Lopes. 2021. Increasing Electrical Muscle Stimulation's Dexterity by means of Back of the Hand Actuation. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. ACM, Yokohama Japan, 1–12. https://doi.org/10.1145/3411764.3445761

[74] Emi Tamaki, Takashi Miyaki, and Jun Rekimoto. 2011. PossessedHand: techniques for controlling human hands using electrical muscles stimuli. In *Proceedings of the 2011 annual conference on Human factors in computing systems - CHI '11*. ACM Press, Vancouver, BC, Canada, 543. https://doi.org/10.1145/1978942.1979018

[75] Sho Tatsuno, Tomohiko Hayakawa, and Masatoshi Ishikawa. 2017. Supportive training system for sports skill acquisition based on electrical stimulation. In *2017 IEEE World Haptics Conference (WHC)*. 466–471. https://doi.org/10.1109/WHC.2017.7989946

[76] Sho Tatsuno, Tomohiko Hayakawa, and Masatoshi Ishikawa. 2017. Trajectory adjustment system for learning based on electrical stimulation. In *Proceedings of the 8th Augmented Human International Conference (AH '17)*. Association for Computing Machinery, New York, NY, USA, 1–4. https://doi.org/10.1145/3041164.3041197

[77] Akira Tamaki Toshiaki Miyamoto, Hiroyuki Kamada and Toshio Moritani. 2016. Low-intensity electrical muscle stimulation induces significant increases in muscle strength and cardiorespiratory fitness. *European Journal of Sport Science* 16, 8 (2016), 1104–1110. https://doi.org/10.1080/17461391.2016.1151944

[78] Steeven Villa, Jasmin Niess, Bettina Eska, Albrecht Schmidt, and Tonja Machulla. 2021. Assisting Motor Skill Transfer for Dance StudentsUsing Wearable Feedback. (2021).

[79] Apostolos Vrontos, Verena Nitsch, and Christopher Brandl. 2024. Electrical Muscle Stimulation for Kinesthetic Feedback in AR/VR: A Systematic Literature

Review. *Multimodal Technologies and Interaction* 8, 2 (Feb. 2024), 7. https://doi.org/10.3390/mti8020007 Number: 2 Publisher: Multidisciplinary Digital Publishing Institute.

[80] Katie P. Wadden, Kristopher De Asis, Cameron S. Mang, Jason L. Neva, Sue Peters, Bimal Lakhani, and Lara A. Boyd. 2017. Predicting Motor Sequence Learning in Individuals with Chronic Stroke. *Neurorehabilitation and neural repair* 31, 1 (Jan. 2017), 95–104. https://doi.org/10.1177/1545968316662526

[81] Matthew P Walker, Tiffany Brakefield, Alexandra Morgan, J Allan Hobson, and Robert Stickgold. 2002. Practice with sleep makes perfect: sleep-dependent motor skill learning. *Neuron* 35, 1 (2002), 205–211. https://doi.org/10.1016/S0896-6273(02)00746-8

[82] Janelle Weaver. 2015. Motor learning unfolds over different timescales in distinct neural systems. *PLoS biology* 13, 12 (2015), e1002313.

[83] Gabriele Wulf and Charles H Shea. 2002. Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychonomic bulletin & review* 9, 2 (2002), 185–211. https://doi.org/10.3758/BF03196276

[84] Y. Youm, R. Y. McMurthy, A. E. Flatt, and T. E. Gillespie. 1978. Kinematics of the wrist. I. An experimental study of radial-ulnar deviation and flexion-extension. *JBJS* 60, 4 (June 1978), 423. https://doi.org/10.2106/00004623-197860040-00001

[85] Shuo Zhou and Norihisa Segawa. 2024. Electrical Muscle Stimulation-Based Approach for Enhancing Hand-eye Coordination Training. In *Extended Abstracts of the 2024 CHI Conference on Human Factors in Computing Systems (CHI EA '24)*. Association for Computing Machinery, New York, NY, USA, 1–6. https://doi.org/10.1145/3613905.3650939

[86] George H. Zimny. 1963. Effects of Direction upon Speed of Mirror-Drawing. *The American Journal of Psychology* 76, 1 (1963), 58–65. https://doi.org/10.2307/1419999 Publisher: University of Illinois Press.