Adaptive Electrical Muscle Stimulation Improves Muscle Memory

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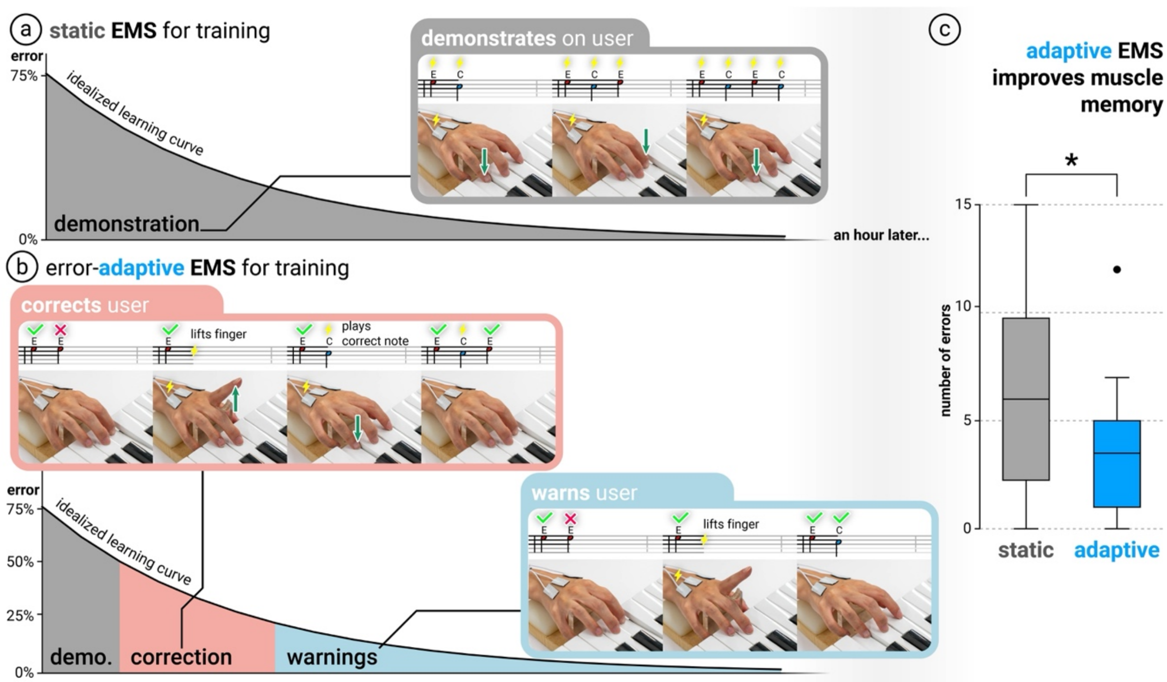

Figure 1: We compared two training strategies to examine how a user learns a sequence of movements by means of electrical muscle stimulation (EMS): (a) *static*-EMS strategy, used by virtually all interactive EMS devices, ignores the user's progress and *always* physically demonstrates the melody by taking over the user's movements; (b) our *adaptive*-EMS strategy dynamically adjusts its guidance based on the user's performance (i.e., when errors are high, it takes over the user's movement; yet, as errors decrease, it only provides corrections or warnings). (c) We found that learning via this adaptive-EMS allowed participants to, unassisted, better remember & playback a sequence of movements— colloquially referred to as "muscle memory".

Abstract

Electrical muscle stimulation (EMS) has been leveraged to assist in learning motor skills by actuating the user's muscles. However, existing systems provide static demonstration—actuating the correct movements, regardless of the user's learning progress. Instead, we contrast two versions of a piano-tutoring system: a conventional EMS setup that moves the participant's fingers to play the sequence of movements correctly, and a novel adaptive-EMS system that changes its guidance strategy based on the participant's performance. The adaptive-EMS dynamically adjusts its guidance: (1) *demonstrate* by playing the entire sequence when errors are frequent; (2) *correct* by lifting incorrect fingers and actuating the correct one when errors are moderate; and (3) *warn* by lifting incorrect fingers when errors are low. We found that adaptive-EMS

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CHI '25, Yokohama, Japan

ACM ISBN 979-8-4007-1394-1/2025/04
https://doi.org/10.1145/3706598.3713676

improved learning outcomes (recall) and was preferred by participants. We believe this approach could inspire new types of physical tutoring systems that promote adaptive over static guidance.

Keywords

electrical muscle stimulation, haptics, agency, learning, motor skills

ACM Reference Format:
Siya Choudhary, Romain Nith, Yun Ho, Jas Brooks, Mithil Guruvugari, and Pedro Lopes. 2025. Adaptive Electrical Muscle Stimulation Improves Muscle Memory. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3706598.3713676

1 Introduction

Learning a new skill requires repeated practice of sequences of movements. For effective motor skill acquisition, beginners need feedback to ensure they are performing the movements correctly. Traditionally, this feedback is provided by teachers through verbal explanations or visual demonstrations. While these methods are widely used, they represent feedback from a third-person perspective [51], focusing on how the movement should *look* rather than how it should *feel*; such feedback requires the presence of an expert teacher, leaving students without guidance during independent practice.

Force-feedback devices have the potential to address this gap by directly moving the user's body, allowing learners to *feel* their body *acting* the correct movements. Extensive research has explored traditional mechanical force-feedback devices like exoskeletons [69, 80], robotic-arms [1], and more [4, 24, 27, 55], but their large size has limited their adoption to research labs or medical settings (e.g., rehabilitation clinics), rather than everyday environments like users' homes [37, 38, 52, 53, 60, 62, 81].

Interactive electrical muscle stimulation (EMS) offers a promising alternative due to its small form factor [37]. By delivering feedback through electrical stimulation, EMS can replace bulky mechanical devices, enabling a range of applications, such as force-feedback in VR/AR [23, 38, 39] or moving a user's wrist to a beat [18]. However, most EMS systems that explore motor skills rely on a *static* guidance strategy [12, 22, 40, 47–49, 53, 70–72], providing the *same* demonstration of the correct movements regardless of the user's *learning progress*. While a starting point, this approach does not adapt to the learner's performance, which prior studies have shown to be critical for skill acquisition [7, 34].

This raises an important HCI question: should EMS systems *also* be designed to *adaptively* teach sequences of movements based on user performance? To answer this, we investigated whether adapting the EMS assistance according to user performance leads to different learning outcomes, i.e., better recall of a sequence of muscle movements—colloquially referred to as "muscle memory". To explore this, we employed a standard learning study design using piano melodies as the movement sequence that participants were asked to memorize. In the *static-EMS* (baseline) condition, EMS consistently guided the participants' movements throughout the learning process. In contrast, our *adaptive*-EMS condition's learning trials adjusted the guidance based on the participant's errors: (1) *demonstrates* by having the EMS play the entire sequence when errors are frequent; (2) *corrects* by having the EMS lift incorrect fingers and actuate the correct one when errors are moderate; and (3) *warns* by having the EMS lift incorrect fingers when errors are low.

In this study we unveiled two key advantages of this adaptive approach: (1) improved learning outcomes, with participants making fewer errors during recall, as depicted in Figure 1; and, (2) participants valued adaptive guidance, finding the system's dynamic adjustments engaging and supportive in their learning. In fact, the majority of participants preferred the adaptive approach over static-EMS, which was often described as disengaging and taxing.

2 Related work

Our work builds on interactive force-feedback systems designed to teach physical skills by directly actuating the user's body to perform target movements, such as playing the correct piano key. We take inspiration from learning sciences, specifically the idea of *adaptive training* in computer-based education. Adaptive training considers the learner's performance to provide dynamic feedback or adjust task difficulties based on learners' learning curves (e.g., their past errors), and it has proven to be an efficient training strategy for many domains [34, 43]. Specifically, we turn our attention to emergent interfaces using electrical muscle stimulation and investigate if adaptive strategies improve their outcomes.

2.1 Strategies for motor skill acquisition

Motor skill acquisition typically involves a combination of processes, including error correction [65], movement refinement through repetition [2], and sequencing actions into smooth patterns [54]. As emphasized by neuroscience, these processes become more prominent as learners progress, reflecting the dynamic nature of skill development [67, 68]. Breaking down complex motor skills into smaller, manageable units—known as "chunking"—further enhances recall and execution [15]. These insights have shaped teaching strategies, with *adaptive guidance* emerging as particularly effective [44].

The most straightforward approach is to provide the learner with *static* guidance, i.e., providing feedback that assists with rote memorization by delivering consistent feedback regardless of progress (e.g., in the case of a motor movement sequence this can be done by repeatedly demonstrating a complete sequence of movements—as we will see later in the baseline condition of our study). The advantage of this type of guidance strategy is that it offers predictable, clear feedback that can be beneficial for beginners building basic skills [22, 49, 59]. As we will detail later, these static strategies have been already explored with force-feedback, even in the case of muscle stimulation [48].

In contrast, *adaptive guidance* tailors feedback to the learner's proficiency and needs, which can be approximated, for instance, by analyzing the learner's errors [31]. The advantage of adaptive methods is that they typically can enhance learning outcomes and reduce cognitive load by addressing the learner's needs in real-time [6]. While adaptive strategies have been featured prominently in computer-based learning [7, 21], using these in force-feedback is still an emergent area—importantly, these have not been used in the case of electrical muscle stimulation, which is the central focus of our contribution.

Moreover, research on embodied cognition highlights the importance of integrating bodily-actions into learning, suggesting that directed/spontaneous actions can deepen understanding and retention [10]. Building on these principles, our work examines the impact of adaptive guidance on learning of sequences of movements with an EMS-based interface.

2.2 Force-feedback: from large mechanical-devices to wearable electrical muscle stimulation (EMS)

One way that researchers in HCI have explored support learning physical movements is via force-feedback (e.g., for practicing virtual surgeries [50, 55, 77], to learn to operate virtual machinery [56], and so forth). It is also worth noting that researchers are also many exploring avenues beyond traditional force-feedback, such as passive haptic learning [28, 29, 46] or even methods that forego haptics entirely [43, 66]. However, our work specifically focuses on improving learning based only on force-feedback—with a particular emphasis on the miniaturized force-feedback afforded by EMS.

For a force-feedback device to successfully guide users in a movement, it must be strong enough to physically intervene in the movement. Thus, the traditional ways to achieve force-feedback were historically limited to large mechanical devices, such as exoskeletons [25], pneumatics [14], or robotics [13, 58]—this restricts their use to specialized environments (e.g., labs, stationary infrastructure) and does not enable portable use. In contrast, our focus is on electrical muscle stimulation (EMS), which offers an alternative due to its wearability. In HCI, researchers have extensively explored EMS to actuate various body parts, e.g., fingers [3, 33, 47, 78], wrists [12, 20, 79], arms [38], and even neck [72]—all while maintaining this highly wearable form-factor.

2.3 EMS for learning

As EMS intervenes in the user's muscles *directly*, there has been interest in investigating its impact on interactive learning [19, 26, 48, 49, 73]. For example, Niijima et al. showed that participants could learn to play tremolo effects on the piano by leveraging EMS to rotate their wrists rapidly [49]. In this case, the EMS demonstrated the correct wrist movement without any additional instructions from a teacher. While there were no sequences to be learned, participants learning with EMS were able to perform the tremolo technique for longer compared to the ones without EMS. Similarly, Ebisu et al. explored EMS to teach rhythms (contracting the muscle with the right timing), finding that for half of their participants, the timing-accuracy of EMS was able to create the intended rhythm while the participants were assisted by EMS [19]. Moreover, Niijima et al. demonstrated that using EMS to actuate the user's shoulder movement improved beginner's finger technique for playing piano scales correctly [48]—here, participants learned the correct fingering for a scale (playing notes in ascending order, but with specific fingers), while there was a sequence to be learned, the EMS did *not* teach the sequence, EMS only provided a nudge to the shoulder, to indicate when users should "reset" their fingers (i.e., play next note with thumb). Studies have also shown that EMS can be used for sports training. For example, *FootStriker* used EMS to adjust the angle of the user's foot when running, ensuring proper posture [26]. Another system utilized EMS to adjust the user's wrist-rotation for bowling throws, finding an improvement if participants trained only the wrist pose with EMS (throwing with no ball) but not when using EMS while actually throwing the ball [73]. While these demonstrated improved outcomes, they corrected a single motion or posture rather than *sequences of movements*.

To this end, a late-breaking work by Pfeiffer et al. examined the use of different EMS force-feedback conditions to teach users how to operate a control panel in VR, comparing strategies such as repelling users from incorrect targets, moving them closer to correct targets, and both simultaneously. Despite testing these multiple conditions, these strategies were applied in a *static* manner, meaning users experienced *only one* type of feedback in a condition, regardless of their progression or learning curve. While, unfortunately, the authors did not find a significant learning effect between the feedback conditions [57], we still discuss this late-breaking work again in our "strategies" section, given its resonance with our aims.

Prior work is *static*-EMS. Taken together, the studies highlight the potential of EMS for physical skill acquisition, but they share a key limitation: all these studies use *static*-EMS, where the device *always* applies the same feedback, without adapting to the user's learning progress or errors. Instead, we aim to systematically investigate if *adapting* the EMS guidance to user's errors can further enhance learning outcomes.

2.4 Adaptive strategies in haptics

In broader haptic contexts, researchers have identified the limitations of static strategies and have explored adapting both the task parameters and the haptic feedback to better support the learning experience [36, 42, 59, 76].

A popular approach outside of haptics is to adjust the task difficulty, such as adapting the difficulty of a basketball throw [75, 76] or the speed of a piano piece [82]. These approaches often lead to better learning compared to static strategies, as they progressively challenge the learner. However, modifying the task is not always feasible or desirable. By contrast, using haptics allows researchers to implement strategies for a wide range of motor tasks, as it modifies movements rather than altering task parameters, making it a more versatile approach.

To leverage the benefits of haptics, one popular approach is to vary the *level of assistance* provided by the haptic device [20, 51, 61]. Three examples are particularly relevant to our proposal. First, Rowland et al. found that an adaptive strategy improved accuracy in Fitts' law tasks using a force-feedback stylus [61]. Their design not only adjusted the strength of the stylus's force-feedback but also toggled the learning between modes of *guidance* (pushing users towards targets) and *hindrance* (resisting movements away from targets). Second, the aforementioned late-breaking work by Pfeiffer et al. similarly explored these roles of *guidance* and *hindrance*, implemented as "encouraging" (hinting at the correct target) and "preventing" (preventing button presses) [57]. Although they did not find a "learning effect between the feedback conditions," they argued for the value of situations in which EMS can play different

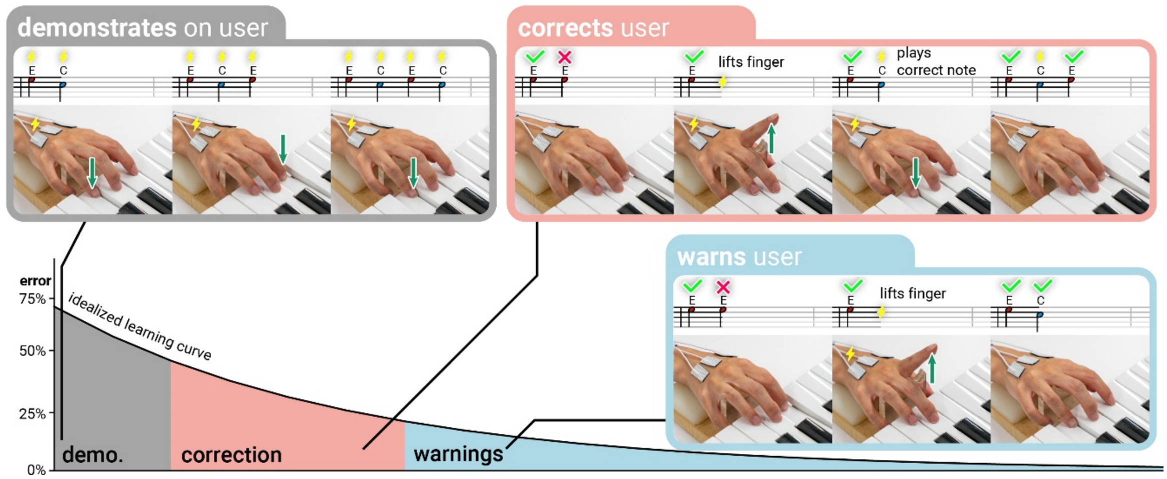

Figure 2: The idea underlying an adaptive strategy to adjust the feedback depending on users' needs. In this instantiation of our concept (which we used in our study), we adjust the amount of EMS-assistance based on the user's error rate—as errors decrease, the EMS intervenes less often. The EMS goes from demonstrating the full melody to only correcting and eventually only warning.

roles, such as encouraging and/or preventing movement. Third, Nishida et al. employed an adaptive strategy in a pair of passively-coupled exoskeleton gloves, where a piano teacher's glove moved the student's fingers [51]. The force was adjusted according to the *user's errors*, with the teacher's input (force) diminishing as errors decreased. While they did not observe improved learning outcomes, they found that participants preferred the force-adaptive condition over the static one. Their findings also revealed possible downsides of adapting the *force* level of a force-feedback intervention, since some participants reported this "inconsistency in intervention pressure caused confusion" [51]—this informed our decision to adapt the type of guidance strategy rather than the force. Although prior research has neither investigated adaptive strategies for EMS nor designed the same adaptation strategy as ours, we drew inspiration from these works that demonstrated the value of adaptive strategies. Finally, outside of the realm of interactive-EMS, clinicians and medical researchers have explored varying the muscle-stimulation parameters for gait-rehabilitation and observed improvements [11, 16, 17, 30, 35]. These examples further support our hypothesis that an adaptive-EMS strategy could outperform static methods used in interactive-EMS systems for teaching sequences of movements.

3 Our proposal: adapt the muscle-guidance to the user's error rate

We take inspiration from the aforementioned insights in learning sciences that have long denoted the process of learning as a *curve* [41] (colloquially referred to as learning curve in HCI), rather than as a static process. Learning sciences suggest that the level of assistance should decrease as the learner's proficiency increases [44]. This presents fertile ground for interactive systems that physically guide the user's muscles, as is the case with electrical muscle stimulation. As such, we ask the question: **Can we improve EMS-based learning by adapting the level of assistance according to the user's errors?** Specifically, as users improve, assistance should decrease, and when they struggle, it should increase.

Current EMS systems typically rely on a static approach, consistently providing the same guidance (e.g., demonstrating correct movements) regardless of users' progress. To address this limitation, we propose an adaptive-EMS strategy that adjusts guidance in real time based on user performance. As shown in Figure 2, this strategy transitions automatically through three phases depending on the user's error rate during their previous recall attempt.

Phase 1: Demonstration Phase. EMS demonstrates an entire movement sequence by actuating the user's body. This mirrors the more traditional static-EMS, offering comprehensive guidance in the early stages of learning or when error rates are high. (In our study implementation we kept users in this phase if they exhibited >50% errors.)

Phase 2. Correction Phase. EMS allows the user to play the sequence of movements but intervenes when they make mistakes by: (1) actuating them to stop the incorrect movement; then, (2) actuating the correct movement in the sequence. (In our study implementation, we stopped incorrect movements by repelling the incorrect finger away from the wrong key, and, then actuating the correct finger to play the correct key. Moreover, in our study implementation we kept users in this phase if they exhibited >50–20% errors.)

Phase 3: Warning Phase. EMS allows the user to play the sequence of movements but intervenes when they make mistakes; yet, it only stops the incorrect movement (no correction). Our rationale is that minimal intervention encourages self-reliance when approximating mastery. (In our implementation, we kept users in this phase if errors were <25%.)

Design rationale. The goal of these phases is to *automatically* and *progressively* reduce EMS intervention as proficiency increases, fostering engagement and self-reliance. The particular thresholds used in our study's implementation for transitioning between phases were informed by extensive pilot testing, so as to balance sufficient time in the initial demonstration phase (to prevent premature frustration) with appropriate progression to the correction and warning phases; future work might choose to refine these thresholds based on task complexity, user feedback, etc.

4 User study

We investigated if an adaptive-EMS strategy could lead to better outcomes when learning a sequence of movements (i.e., better at recalling a sequence of movements they learned). To this end, we implemented a piano learning tutorial that used electrical muscle stimulation to iteratively teach key sequences—our study focuses only on learning sequences of movements and not musical understanding (e.g., no score comprehension, timing, etc.). We compared two conditions: a *static* strategy (emulating how prior work on EMS learning approaches this), and our novel *adaptive*-EMS strategy.

Hypothesis. Our hypothesis was that adapting the strategy to the participants' learning curve (i.e., errors) would best support their learning experience, resulting in fewer errors in a final unassisted recall of the sequence of movements.

Ethics. Our study was approved by our ethics review board (*IRB anonymized for review*).

4.1 Study design

Our study followed the typical *learn-recall* design, in which participants perform a *learning* trial (assisted by EMS) followed by a *recall* trial (unassisted; this is the trial where errors are measured). As is common in these studies, participants perform learn-recall trials until they have mastered the pattern—in our case, until they performed the piece *three times at over 95% correctness* (only one mistake allowed in 24 possible notes). Once participants achieved three correct recalls, they were sent away and asked to return one-hour later for a final interview. Then, we performed a *post-test recall trial*. There was no assistance from EMS, and participants were simply asked to play the movement sequence as best as they could once. This *post-test recall trial* depicted their ability to retain the sequence of muscle movements—colloquially, their "muscle memory" of the finger sequence—after one-hour.

Interface conditions. Participants underwent the aforementioned process twice, once for each condition: *static-EMS* (baseline) or *adaptive-EMS*. The order of the conditions was counterbalanced across participants. In the static-EMS condition, the EMS demonstrated the complete movement sequence by actuating participants' fingers to play it correctly in every learning trial. In the adaptive-EMS condition, for learning trials, the EMS switched between three different strategies depending on the participants' error on the last recall trial (Figure 2): >50% error (or first training trial) caused the EMS to demonstrate the complete sequence (same as baseline); 50%-25% error caused the EMS to ask the participants to play the sequence and only intervened when they made a mistake, in which case it repelled their finger away from the incorrect key and then played the correct key by actuating the correct finger; and, <25% error caused the EMS to only indicate where participants made mistakes by repelling their fingers from the incorrect key, but not by correcting them. Our system announced aloud the guidance strategy (demonstration, correction, warning) at the start of all learning trials.

Data collection. Our main metric was the *post-test recall*—error observed in an unassisted recall *after one-hour*. Moreover, to learn more about participants' subjective experience with adaptive-EMS, we interviewed them at the end of the study, asking them to choose their preferred condition and explain why.

4.2 Apparatus

Our study made use of our custom-designed piano tutorial application, using a MIDI keyboard and an EMS device.

Piano hardware. A MIDI keyboard (*MiDiPLUS*, Classic 25) with a 3D-printed stand to position index, middle, and ring fingers over keys (C, D, E)—this ensured that the EMS was reliable at pressing the correct key. MIDI was received over USB using *Mido* [83] and analyzed in real-time (and logged) to determine the participant's error on a single trial, which in the adaptive condition was used to adjust the strategy of the subsequent learning trial.

Stimulation hardware. Electrical stimulation was delivered to the dominant arm using pre-gelled electrodes (*Syrtenty*, 25.4 × 25.4mm TENS unit pads). The electrodes were connected to a medically compliant electrical stimulator (*HASOMED,* P24), which administered stimulation based on the condition's strategy.

EMS Calibration. Experimenters iteratively calibrated the position of the EMS electrodes to ensure: (1) pain-free operation, and (2) each actuation resulted in a reliable and independent movement of one finger (thus, only one key was pressed per actuation). To achieve this, experimenters employed back-of-the-hand EMS technique [70] when needed. Four independent channels were placed on participants' muscles to flex the index, middle, and ring fingers as well as extend all three at the same time (for adaptive-EMS' warning mode, retracting finger).

4.3 Melodies

We developed two distinct melodies (Figure 3) of comparable difficulty and suited to EMS' precision. To ensure stability in the EMS actuations, the movement sequences were limited to three notes—C, D, and E—played via index, middle, and ring fingers—generally considered to be the most reliable fingers when moved by means of EMS [32, 70].

Melody design. Each melody consisted of 24 notes, forming sequences that were intentionally challenging for non-trained musicians due to their length and structure. Both contained six repeating sub-patterns (groups of adjacent notes that repeat), balancing their structural characteristics. These sequences were generated using a random number generator to ensure that both had similar levels of entropy, a measure of randomness, which we calculated by assessing the probability of each note's occurrence within the overall pattern. The entropy values are 1.585 for melody 1 and 1.563 for melody 2—a comparable complexity. Importantly, the notes were *never visually shown* to participants, **they only learned the movement sequences by means of EMS feedback.**

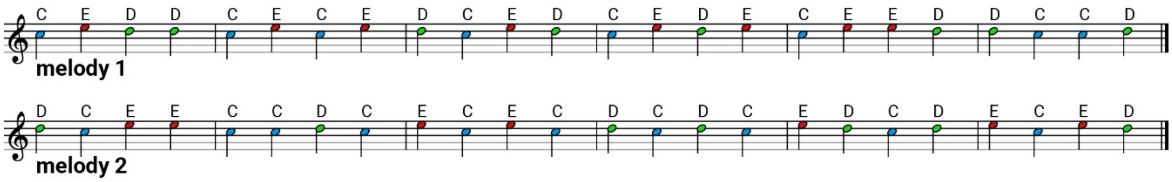

Figure 3: The two full melodies for our study with notes color-coded for visual clarity (never shown visually to participants).

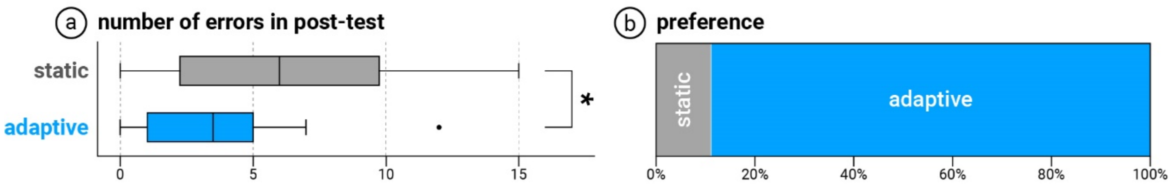

Figure 4: (a) Improved error recall with adaptive-EMS compared to static-EMS. (b) Participants' preference for adaptive-EMS.

4.4 Participants

We recruited 20 participants; however, two were disqualified: one failed the pre-test, and the other could not be reached for their post-test recall. Therefore, in this section, we analyze the data from the remaining 18 qualified participants (M = 25.8 years old, SD = 7.9), consisting of eight female and ten male participants. Only one participant was left-handed. All participants received $50 USD as compensation for their time.

Pre-test. To ensure participants were not highly skilled at piano, we conducted a pre-test, where they recalled a sequence of 10 notes demonstrated once by the experimenter. If participants performed >60% correct, they did *not* qualify. Only one participant was disqualified with a 90% recall (later revealed to be a trained musician). Of the qualified participants, we found an average of 55.3% of errors (SD = 14.6%) on the pre-test. Most qualified participants had little to no exposure to music playing (M = 0.75 years of music playing, SD = 1.73).

4.5 Results from learning with adaptive-EMS vs. static-EMS

Learning outcome. Figure 4 (a) depicts our main finding. We found that the number of errors in the post-test recall (i.e., play the movement sequence one-hour after the learning session was completed) was **significantly lower** with *adaptive-EMS* (M = 3.67, SD = 3.14) than *static-EMS* (M = 6.22, SD = 4.26), $t(17)$ = 2.49, p = 0.023 (Bonferroni corrected). This suggests that participants were able to better recall the sequence they learned through *adaptive-EMS*.

Preference. We found that participants' preference over the two interface conditions was aligned with this result. We found that ~**90% of participants** (16 out of 18) **preferred adaptive-EMS** for learning.

Number of trials. Finally, we found no difference ($t(17)$ = 0.99, p = 0.338, Bonferroni corrected) in the number of learning trials required to master the sequence (i.e., >95% accuracy during learn-recall phase) between adaptive-EMS (M=18.8, SD=6.24) and static-EMS (M=21.0, SD =9.46). This suggests that the improvement seen in adaptive-EMS is unlikely to be attributed only to the length of training, as both conditions required a similar number of trials.

4.6 Participants' subjective experience with adaptive- vs. static-EMS

We transcribed participants' comments when detailing their experience in the study, which we analyze next.

Perceived impact of condition on learning. Nine participants (P1-3, P6-9, P12, P14) highlighted that the adaptive-EMS condition enhanced their learning experience. They particularly valued the immediate corrections, which helped identify and rectify mistakes promptly. Unlike the static-EMS condition, which often forced participants to depend on "rote memorization" (P1, P10), the adaptive system facilitated real-time adjustments, leading to a more dynamic and exploratory learning process. Participants described adaptive-EMS as a "beneficial tool for learning" (P1) and appreciated how it facilitated a "more natural learning progression" (P2). Some specifically noted the usefulness of the warning mode in identifying mistakes (P3) and how adaptive-EMS "reduced guesswork" (P9), helping them identify and improve mistakes (P6). Others emphasized the exploratory nature it encouraged, with P7 and P8 describing how adaptive-EMS allowed them to "experiment and adjust on the fly".

Engaged learning with adaptive-EMS. Without being prompted, seven participants (P1, P2, P8, P10, P11, P13, P15) specifically stated that adaptive-EMS was more engaging than static-EMS. For instance, P11 described the increased "involvement" as having "significantly improved the learning experience," and P15 referred to it as "handholding at each step". Additionally, participants appreciated how adaptive-EMS was "beneficial [. . .] to adjust to progress and step back if needed". On average, participants switched modes seven times (SD = 3.46), reflecting varied learning needs. Figure 5 illustrates examples of learning curves leading to different experiences: (a) P12 depicts the most-straightforward learning curve, only experiencing each mode once; (b) P11 depicts the average example, with six mode switches, typically experiencing more switches

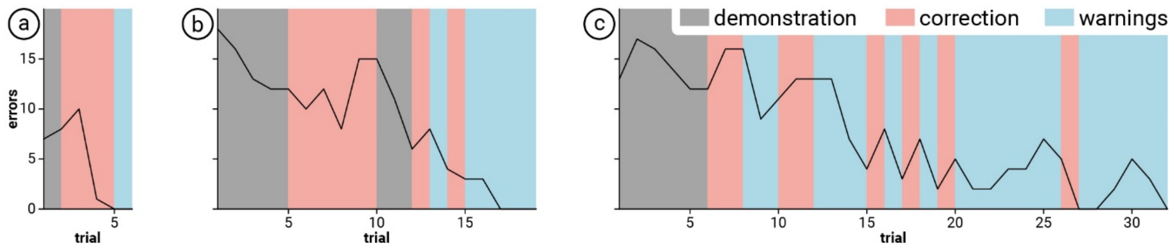

Figure 5: (a) Most-straightforward learning curve (P12). (b) Learning curve with average number of switches (P11). (c) A case with many switches in guidance strategy (P2).

towards the second half; and (c) P2 depicts the most extreme, experiencing twelve switches.

Frustration with static-EMS. Five participants (P2, P3, P8, P11, P13) expressed dissatisfaction with the static-EMS condition, citing its reliance on rote memorization and the lack of control or active engagement in the learning process. Participants found the passive, repetitive nature of this condition to be less effective and less motivating compared to the adaptive-EMS. P2 noted that static-EMS make the learning process more taxing, demanding much more active memorization. P3 found the static condition awkward and difficult to remember at first. P8 and P11 described it as disengaging, with P8 expressing frustration and P11 highlighting a loss of autonomy due to repetitive nature of the guidance. P13 further emphasized that the lack of dynamic interaction hindered their learning process.

Wish for customizing adaptive-EMS. Five participants (P3, P5-7, P10) expressed a desire for greater control over transitions between phases in adaptive-EMS. They felt that the system sometimes advanced too quickly into corrective mode. Specific suggestions included manually controlling when to move forward (P3 and P5).

Initial confusion with adaptive-EMS' corrections: Despite the overall preference for adaptive-EMS, six participants (P2, P4, P5, P7, P10, P13) reported "initial confusion" with adaptive-EMS correction feedback, particularly during transitions between correction and warning phases. Three found corrections mid-pattern disruptive (P10, P13, P5). To this end, P5 suggested replaying surround notes alongside the correction for better context, while P10 & P13 suggested that more guidance can reduce confusion (P10, P13).

Perceived value of EMS for learning. Nine participants (P1, P3, P5-8, P11-13) stated that EMS had utility for learning, with six specifically praising adaptive-EMS. Participants often compared EMS favorably to traditional teaching methods, such as instructors or videos. P1 noted the independence provided by EMS, preferring it over traditional teaching because "it can be performed alone"; P5 (and similarly P6) noted that either EMS conditions felt "better than following a video"; P12 stated that "[adaptive-EMS] was far easier to use [than videos]"; P11 (and similarly P13) stated that EMS felt "valuable and exciting for learning tasks". However, one participant (P7) expressed reservations about its potential effectiveness for teaching rhythmic tasks (which our study did not include, since movements were recalled without a metronome) but imagined usefulness in non-rhythmic tasks.

5 Discussion of findings

Our study demonstrated that adaptive-EMS improved learning outcomes compared to static-EMS, as evidenced by fewer errors measured in the post-test recall. This highlights the potential of adaptive systems to enhance movement sequence acquisition by dynamically adjusting haptic feedback to real-time learning needs. This finding aligns with prior research emphasizing that adaptive guidance, when tailored to the learner's proficiency, facilitates more effective learning by addressing specific deficiencies rather than providing generic instruction [5].

Interestingly, the number of learning trials required to master the sequence did not differ significantly between conditions. This suggests that the benefits of adaptive-EMS stem not from extended practice but from the *nature of its feedback.* Such results are consistent with Tennyson & Park's early findings [74], which highlight that tailored guidance improves task-specific performance without extending training duration.

Participants overwhelmingly preferred adaptive-EMS, citing its usability and effectiveness. Unlike static-EMS, which was described as repetitive and disengaging, adaptive-EMS fostered a more engaging learning environment by enabling participants to "experiment and adjust on the fly" (P7, P8). This resonates with learning theories, such as those proposed by Merrill [45], which emphasize the importance of active engagement and learner agency in skill acquisition. Furthermore, the dynamic nature of adaptive-EMS echoes Bell & Kozlowski's observation that interactive systems allowing experimentation foster deeper cognitive engagement and motivation [6, 31].

Corrections provided by adaptive-EMS were particularly valued, as they allowed participants to promptly rectify mistakes and avoid reliance on rote memorization. This aligns with broader research finding that immediate, context-aware feedback reduces error accumulation and supports long-term retention [9] as well as research indicating that feedback fosters skill acquisition more effectively when it supports error correction while encouraging self-reliance [8]. However, some participants noted that transitions between learning phases (e.g., demonstrations to corrections) felt premature. This concern is supported by evidence suggesting that pacing and timing of feedback are critical for fostering confidence and minimizing frustration [74].

Despite the emergent nature of EMS as an interface, our findings corroborate broader theories advocating for active engagement and adaptive feedback as foundational to effective skill acquisition [45,

Figure 6: Adaptive-EMS applied to learning a sequence of button presses, such as in Morse code. In this example, the entire the word "mind" is played back when the user makes a mistake only in the final letter, this provides more context for the adaptive-correction.

64]. By integrating participants' design suggestions—such as user-controlled transitions—we can align future iterations of adaptive-EMS more closely with these theoretical frameworks, ensuring the system remains both effective and learner-centric. Additionally, this approach could address learner variability by allowing self-paced progression.

6 Design challenges and suggestions

While our study demonstrated that error-adaptive strategies enhance muscle memory compared to traditional static approaches in EMS-based systems, feedback from participants revealed design challenges that warrant attention from future researchers: (1) *Contextual clarity in corrections:* Participants reported that corrections in the adaptive phase lacked sufficient context, leading to occasional confusion. (2) *Customizing phase transition:* Participants expressed a desire for greater control over transitioning between learning phases. (3) *Task interference:* EMS corrections could occasionally disrupt performance, e.g., if the same muscles used for warnings are required for executing the target movements.

In the following sections, we expand on each challenge by identifying the issue, illustrating a possible solution in the context of our study (i.e., piano), and illustrating a broader application of these suggestions to other domains. By doing so, we aim to demonstrate the versatility of our adaptive-EMS technique.

6.1 Providing more context when delivering movement corrections (design suggestion from P5)

Participants highlighted initial confusion with adaptive-EMS' corrections and mentioned the need for context (namely P5). Instead of replaying only the correct movement, adaptive-EMS could be modified to replay a meaningful *chunk* of the sequence, helping users situate their correction within the broader context. For example, in piano tutoring, rather than merely lifting the user's finger from an incorrect note and playing the correct one, adaptive-EMS could replay the entire musical section containing the error (e.g., a bar), offering greater clarity. Figure 6 takes this idea to a new domain and illustrates this design solution in a Morse code application. In it, when the user makes an error in the letter "d" while typing the word "mind," the system demonstrates the entire pattern for "mind" rather than correcting only one letter.

6.2 Allowing users to manually control the learning phases (design suggestion from P3 & P5)

In our study, adaptive guidance progressed *automatically* based on error rate. Participants noted they might want to manually switch phases at times. Adaptive-EMS could be modified to allow users to override the automated phase transitions. This could be valuable for learning physical skills where progression requires more than just adapting to error rates; it could also depend on the user's confidence. For instance, Figure 7 illustrates learning a dance-choreography with adaptive-EMS. Here, the system automatically advances phases, but the user dials it back via their smartphone.

6.3 Reducing potential interferences caused by corrective movements (as experienced by P10 & P13)

Adaptive-EMS delivers real-time corrections as users learn, but these corrections can sometimes interfere with the primary-task (as stated by P10 & P13). This arises when warning stimulate the same limb that is already in use for the task, potentially causing further errors. While this was not the case in our user study (since moving the finger away from the piano did not press other keys), this would be the case for a task like playing the theremin[1], as depicted in Figure 8. To address this, warnings could be delivered via another body part to avoid disrupting the task-relevant limb. While playing a theremin, delivering a warning in the hand that makes a mistake, could cause pitch/volume changes. Figure 8 shows an alternative using head actuation [72] to direct the user's attention to the hand that made the mistake.

7 Conclusions and future work

We proposed and evaluated an adaptive strategy for learning sequences of movements using electrical muscle stimulation (EMS). We demonstrated it outperformed the traditional approach (static-EMS), improving unassisted recall of movement sequences one-hour after learning and being preferred by the majority of participants. Future research building our own groundwork might explore new renditions of adaptive-EMS, for instance, studying it in tasks that require complex coordination in multiple areas of the body. Finally, our results highlight the potential of adaptive over static guidance

[1]The theremin is a non-contact electronic instrument where the right-hand controls pitch and the left-hand adjusts volume.

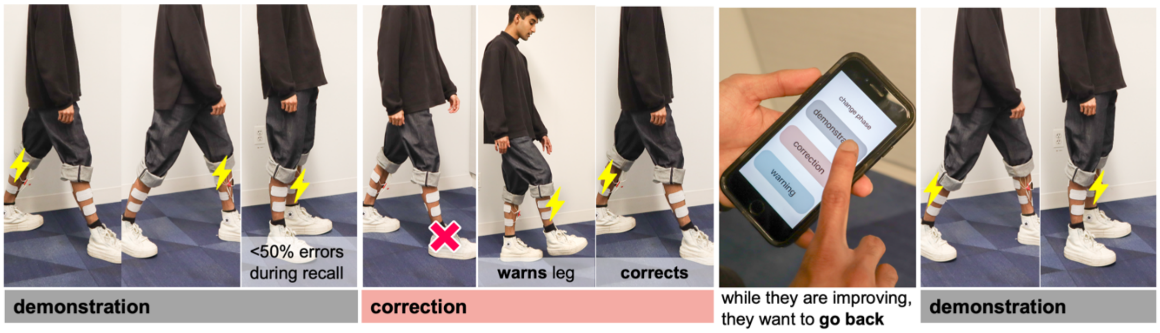

Figure 7: Adaptive-EMS applied to learning a dance choreography. In this example, the adaptive guidance progresses to the correction mode automatically, but it allows the user to dial it back to the demonstration mode.

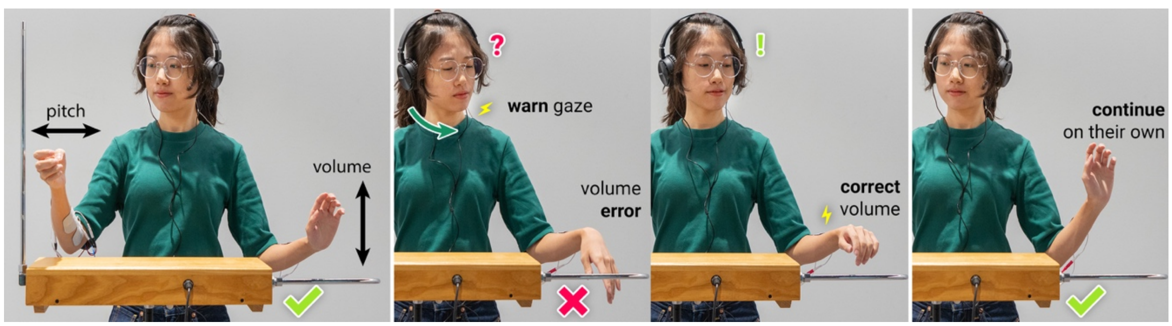

Figure 8: Adaptive-EMS applied to learning to play the theremin. Here, we apply an alternative design for the warning mode—EMS actuated the head to look at the hand that caused the error—to prevent interference with the primary task.

in physical tutoring systems. This approach could be extended to other force-feedback systems by incorporating dynamic adjustments (e.g., force-intensity) and additional measures of progression (e.g., cognitive-load).

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