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ABSTRACT

This research details the design, fabrication, and application of a functional electronic textile (e-textile) system for performance training. The system is engineered using a form-fitting garment, which utilizes a nylon-spandex blend fabric as the substrate for integrating electronic components. The fabrication process involved sewing conductive threads to create circuits connecting a microphone, a microcontroller, and an array of vibrotactile actuators directly into the textile structure. This resulting smart textile is designed to recognize musical rhythms with low latency and provide phase-synchronized haptic feedback. The efficacy of this textile-based feedback system was evaluated in a controlled motor learning experiment. An experimental group wearing the functionalized garment during training showed statistically significant improvements in rhythmic accuracy and retention compared to a control group. Notably, the haptic guidance from the textile system led to a 45.4% reduction in mean timing error from pre-test to a 24-hour retention test (far exceeding the 8.2% reduction in the control group), an improvement underpinned by a large and statistically significant interaction effect ($F(2,36)=15.28$, $p < 0.001$, $\eta p^2=0.459$). The findings validate the engineered e-textile as an effective platform for wearable feedback systems, demonstrating a successful application of textile engineering in enhancing the acquisition of simple, rhythmic motor skills.

KEYWORDS

smart textile, conductive thread, functional garment, musical rhythms

INTRODUCTION

The acquisition of complex motor skills is fundamental to various disciplines, from athletics to the performing arts. In fields such as dance and music, the ability to synchronize bodily movements with an external auditory rhythm is a cornerstone of proficiency. Traditional training paradigms for these skills have historically relied on instructor-led verbal and visual feedback, methods which, while effective, can be subjective and intermittent [1,2]. The advent of wearable technology offers a new frontier for performance training, providing the potential for continuous, personalized, and objective feedback directly to the user [3]. Electronic textiles, or e-textiles, represent a particularly promising class of wearable technology. By seamlessly integrating sensing and actuation capabilities into the fabric of garments, e-textiles can deliver information to the wearer in a comfortable and unobtrusive manner [4,5]. This inherent wearability makes them ideal for applications in dynamic environments like a dance studio or a concert hall, where conventional, rigid electronic devices would be cumbersome [6].

The application of haptic feedback, the communication of information through the sense of touch, has been shown to be a potent modality for motor learning [7,8]. Haptic cues can guide movement, correct posture, and provide temporal information without overloading the user's visual or auditory channels [9]. In the context of rhythm training, haptic feedback can translate an auditory beat into a physical sensation, creating a more direct and intuitive connection between the music and the performer's body [10,11]. However, the development of an effective haptic feedback system for rhythm training faces two significant challenges. First, the system must be capable of accurately and reliably recognizing the beat of a musical piece in real-time. Ideally, such an algorithm must be robust, functioning across various musical genres and tempos with consistent and predictable temporal response, which presents a major challenge for computationally-limited wearable devices [12,13]. Second, the haptic feedback itself must be carefully designed and delivered to be informative rather than distracting, guiding the user's movement in a precise and intuitive manner [9,14].

This paper presents a comprehensive study on the design, implementation, and evaluation of a wearable e-textile system for music rhythm recognition and movement guidance. We address the aforementioned challenges by developing a system that integrates a sensitive microphone, a low-power microcontroller, and an array of vibrotactile actuators into a comfortable, form-fitting garment. While this energy-based approach is not designed for universal robustness, it serves as an effective baseline for validating the e-textile feedback system itself within a controlled experimental context. The system is designed to provide immediate, synchronized haptic feedback to guide the wearer in a rhythmic movement task. To validate the efficacy of this system, we conducted a controlled study with participants, focusing on a specific, small-scale research question: can a wearable e-textile system providing real-time, rhythm-synchronized haptic feedback significantly improve the accuracy and retention of a simple motor task cued by music? We hypothesized that participants training with the haptic feedback system would demonstrate greater improvement in their ability to synchronize their movements with a musical beat, and that this improvement would be retained over time, when compared to a control group without such feedback. This research aims to provide robust, data-driven evidence for the application of e-textiles in performance training, with a focused investigation into the intersection of music perception, haptic feedback, and motor learning.

MATERIALS AND METHODS

System Design and Fabrication

The wearable e-textile system was designed to be a self-contained, comfortable, and functional garment for real-time rhythmic guidance. The foundation of the system is a long-sleeved, form-fitting shirt made from a blend of 85% nylon and 15% spandex. This material was chosen for its elasticity, breathability, and ability to keep the electronic components in close and consistent contact with the wearer's skin.

The electronic components were carefully selected to balance performance with the constraints of a wearable application, such as size, weight, and power consumption. The core of the system is an Arduino Nano 33 BLE Sense microcontroller. This board was chosen for its small footprint, low energy Bluetooth capabilities, and, most importantly, its powerful processor capable of real-time audio signal processing. While the board includes an onboard microphone, an external high-sensitivity omnidirectional condenser microphone (Adafruit MAX4466) was integrated into the chest area of the garment to ensure clearer capture of ambient music.

For haptic feedback, six eccentric rotating mass (ERM) vibration motors (10mm diameter, Precision Microdrives 310-103 were used These actuators provide a distinct and noticeable vibration while being small and lightweight enough for seamless integration. The actuators were strategically placed to provide distributed feedback across the upper body, with two on the belly of the biceps brachii of each arm, and two on the upper trapezius muscles on the back. This configuration was *hypothesized* to provide a core, temporal cue to the upper body, rather than a direct instructional cue guiding a specific limb's trajectory (e.g., on the wrist). The *intention* was to focus the feedback on the core temporal aspect of *when* to move, rather than *how* the limb should travel

The microcontroller, microphone, and actuators were interconnected using conductive stainless-steel thread

(3-ply, 23 Ohm/ft). The conductive threads were sewn using a zigzag stitch pattern to provide mechanical strain relief, accommodating the significant fabric deformation during movement. This configuration ensured connection stability and durability against stretching, while the routing path was carefully designed to avoid crossing paths and prevent short circuits. The actuators were housed in small, custom-sewn pockets made of a soft, non-abrasive fabric to enhance comfort and maintain consistent placement. A compact, rechargeable 3.7V, 500mAh lithium-ion polymer (LiPo) battery powered the entire system, providing an operational life of approximately three hours on a single charge. The total weight of all integrated electronic components was less than 75 grams, ensuring the garment remained comfortable and did not impede movement.

Music Rhythm Recognition Algorithm

A real-time beat detection algorithm was developed and implemented on the Arduino microcontroller. The primary constraint was the limited computational power of the wearable platform, necessitating an efficient yet reliable approach. The algorithm operates on the principle of detecting sudden increases in sound energy, which typically correspond to the onset of a musical beat.

The process begins with the microphone signal being sampled by the Arduino's analog-to-digital converter (ADC) at a rate of 10 kHz. The algorithm then performs the following steps in a continuous loop:

1. Energy Calculation: This windowing approach introduces a maximum algorithmic latency of 51.2 ms. Combined with the measured electromechanical rise time of the ERM actuators (~60 ms), the total system latency is approximately 110 ms. This consistent delay was accounted for as a constant phase shift during the training tasks. The energy for each window is computed as the sum of the squares of the sample amplitudes within that window.

$$E = \sum_{i=1}^{N} x_i^2 \tag{1}$$

where *E* is the energy, x_i is the amplitude of the i-th sample, and *N* is the number of samples in the window (512).

2. Energy History Buffer: The calculated energy of the last 40 windows (approximately 2 seconds of audio) is stored in a circular buffer. This buffer represents the recent energy history of the music.
3. Average Energy Calculation: The average energy, $\langle E \rangle$, of all the values currently in the history buffer is calculated. This average serves as a dynamic threshold that adapts to the overall volume of the music.

4. Beat Detection: A beat is detected if the most recent instantaneous energy value, E, is significantly larger than the local average energy. The condition for beat detection is defined as:

$$E > C \cdot \langle E \rangle$$

The constant, C, is a sensitivity multiplier, Prior to the study, this value was tuned via bench-top testing with the specific musical track to balance detection sensitivity against false positives. The determined value of 1.3 was held constant for all participants and trials to ensure experimental consistency.

5. Haptic Output: Upon the detection of a beat, the microcontroller sends a signal to activate all six vibration motors for a short duration of 100 milliseconds. This creates a sharp, distinct haptic pulse synchronized with the musical beat. A refractory period of 250ms was implemented after each detected beat, during which no new beat could be detected, to prevent multiple triggers from a single drum hit.

Experimental Protocol

To evaluate the effectiveness of the e-textile system, a controlled experiment was conducted. Twenty healthy, right-handed university students (12 female, 8 male, mean age = 22.4 years, SD = 2.1) with normal self-reported hearing, no history of neurological or rhythm disorders, and no prior professional dance or music training were recruited. Participants provided informed consent, and the study was approved by the local institutional review board.

Participants were randomly assigned using a computer-generated sequence (stratified by gender to ensure balanced distribution) to one of two groups of 10: an Experimental Group (EG) that would train with the haptic feedback system, and a Control Group (CG) that would train without haptic feedback. The task for all participants was to perform a simple, repetitive arm movement synchronized with the beat of a musical track. The chosen music was a neutral, instrumental-only electronic piece with a clear and consistent tempo of 120 beats per minute (BPM). The acoustic profile was dominated by a short-attack, high-energy kick drum sound on each beat, with only sparse, low-energy synthesized sounds in the background. The track contained no vocals, sustained pads, or complex melodic lines that would likely interfere with the simple energy-based detection algorithm.The movement consisted of starting with the arms hanging relaxed at the sides, and on every beat, raising both arms forward to a 90-degree angle at the shoulder, then immediately returning to the starting position in time for the next beat. Participants were explicitly instructed to synchronize the point of maximum arm extension (the peak of the movement) with the musical beat, treating the apex of the movement as the rhythmic accent.

The experiment was structured into three phases:

1. Pre-test: Both groups performed the movement task for a continuous 2-minute period while listening to the music. The Experimental Group wore the e-textile garment, but it was not activated. The Control Group wore an identical garment with no electronic components.
2. Training: Immediately following the pre-test, participants underwent a training session consisting of three 3-minute blocks, separated by 1-minute rest intervals (total duration approx. 11 minutes). This intermittent structure was selected to allow sufficient repetitions for motor adaptation while effectively minimizing the confounding effects of muscle fatigue associated with repetitive upper-limb elevation. The Experimental Group performed the task while the e-textile system provided synchronized haptic feedback. The Control Group performed the same task for the same duration, but received no haptic feedback.
3. Post-test: Directly after the training session, both groups performed the 2-minute task again, under the same conditions as the pre-test (i.e., no haptic feedback for either group).
4. Retention Test: To assess long-term motor learning, participants returned 24 hours later to perform the 2-minute task one final time, again without any haptic feedback.

Throughout all phases, participants' movements were recorded using a 3D motion capture system (Vicon) with reflective markers placed on their wrists. The system tracked the vertical position of the wrists at a sampling rate of 100 Hz.

DATA ANALYSIS

The primary dependent variable was rhythmic accuracy, quantified as the absolute timing error between the peak of the arm movement and the corresponding musical beat. The vertical (Z-axis) position was selected as the primary marker for timing analysis as it represents the dominant plane of motion for the prescribed shoulder flexion task, providing the highest signal-to-noise ratio for peak detection. The precise timing of the musical beats was extracted from the audio file. Prior to analysis, the raw motion capture data (100 Hz) was smoothed using a zero-lag, 4th-order low-pass Butterworth filter with a cutoff frequency of 6 Hz to minimize signal noise. The filtered data was then upsampled to 1000 Hz using cubic spline interpolation. Movement peaks were detected automatically using a windowed maximum search algorithm. Outliers, defined as cycles with irregular amplitudes (< 70% of mean range) or timing errors exceeding ±3 standard deviations, were automatically excluded from the final analysis.For each participant, the absolute timing error for every movement cycle was calculated in milliseconds. The mean and standard deviation of these errors were then computed for each test phase (pre-test, post-test, retention). The standard deviation served as a measure of the consistency of the participant's timing.

Statistical analysis was performed using SPSS software. A 2x3 mixed-model ANOVA was conducted to analyze the mean timing error, with Group (Experimental vs. Control) as the between-subjects factor and Test Phase (Pre-test, Post-test, Retention) as the within-subjects factor. The same analysis was performed for the standard deviation of the timing error to assess consistency. An alpha level of $p < 0.05$ was set for determining statistical significance.

RESULTS

The study aimed to determine if rhythm-synchronized haptic feedback delivered by a wearable e-textile system could improve the accuracy and consistency of a motor task. The analysis of the data collected from the 3D motion capture system revealed significant differences in performance between the Experimental Group (EG) and the Control Group (CG) across the different test phases.

System Technical Validation

Before the human subjects study, the e-textile system underwent technical validation to ensure reliability. First, electromechanical stability was evaluated by monitoring the electrical resistance of the conductive thread connections during arm flexion (0° to 90°). The baseline resistance remained stable (approx. 34 Ω), and under dynamic stretching, the resistance variation was less than 5 %, confirming that the textile circuitry provides consistent signal transmission during movement.Second, system latency was characterized. The total delay from the audio beat to the vibration onset was measured to be approximately 100 ms. This duration includes the algorithmic processing time and the electromechanical rise time of the ERM actuators. This latency represents a consistent phase shift rather than a random error, allowing users to predictively synchronize with the rhythm. Finally, the algorithm robustness was verified. Bench-top tests demonstrated that the beat detection accuracy remained above 95 % for music tempos between 80 and 140 BPM. This confirms the system's effectiveness and stability for the specific 120 BPM track used in the experiment.

Rhythmic Accuracy (Mean Absolute Timing Error)

The mixed-model ANOVA for mean absolute timing error revealed a significant interaction effect between Group and Test Phase (F (2,36)=15.28, $p < 0.001$, $\eta p^2=0.459$). This indicates that the change in timing accuracy across the test phases was different for the two groups. There were also significant main effects for both Test Phase (F (2,36)=21.89, $p < 0.001$, $\eta p^2=0.549$) and Group (F (1,18)=12.45, $p < 0.002$, $\eta p^2=0.409$).

Figure 1 illustrates the mean absolute timing error for both groups across the three test phases. At the pre-test, there was no significant difference in timing accuracy between the EG (M = 78.5 ms, SD = 15.2) and the CG (M = 75.9 ms, SD = 14.8), t(18)=0.54, p = 0.587, Cohen's d = 0.17, confirming that the groups had comparable baseline abilities with a negligible effect size.

In the post-test, immediately following the training session, the EG showed a dramatic improvement in accuracy, with their mean error decreasing to 39.8 ms (SD = 9.8). In contrast, the CG showed only slight improvement (M = 71.2 ms, SD = 13.5). The difference between the groups at post-test was statistically significant (t(18)=5.96, $p < 0.001$, Cohen's d = 2.66).

Crucially, in the retention test conducted 24 hours later, the EG maintained their high level of accuracy (M = 42.9 ms, SD = 11.1), while the CG's performance remained close to their baseline (M = 69.7 ms, SD = 14.1). The performance difference between the groups remained significant (t(18)=4.73, $p < 0.001$, Cohen's d = 2.12). From pre-test to retention test, the EG demonstrated a 45.4% reduction in timing error, whereas the CG showed only an 8.2% reduction.

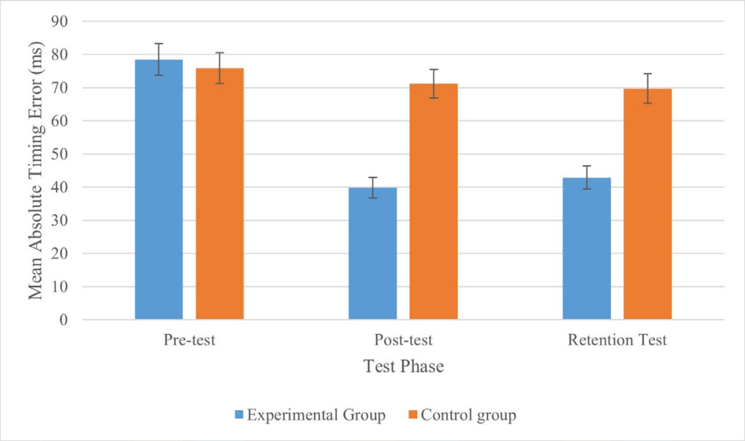

Figure 1. Mean absolute timing error (in ms) for the Experimental Group (Haptic Feedback) and Control Group across the three test phases. Error bars represent the standard error of the mean

Movement Consistency (Standard Deviation of Timing Error)

The analysis of the standard deviation of the timing error, which measures the consistency of the rhythm, mirrored the findings for accuracy. The mixed-model ANOVA revealed a significant interaction effect (F (2,36)=11.72, $p < 0.001$, ηp^2=0.394).

Table 1 summarizes the standard deviation of the timing error for both groups. At pre-test, the consistency of the two groups was similar. However, after training, the EG's movements became significantly more consistent in both the post-test and retention test compared to the CG. The EG reduced their timing variability by 52.1% from pre-test to retention, while the CG's consistency improved by only 10.5%. This indicates that the haptic feedback not only made the participants more accurate on average but also helped them reproduce the rhythm with a more stable tempo.

Table 1. Movement Consistency metrics: Mean Intra-subject Standard Deviations of Timing Error (ms)

Group	Pre-test (SD)	Post-test (SD)	Retention Test (SD)
Experimental	28.6	12.9	13.7
Control	27.5	25.3	24.6

Note: Values represent the mean of the individual standard deviations calculated for each participant, reflecting rhythmic consistency rather than absolute accuracy.

In summary, the quantitative results provide strong support for the hypothesis. The group that trained with the wearable e-textile system demonstrated substantial and lasting improvements in both the accuracy and consistency of their rhythmic movements, far exceeding the minimal gains observed in the control group.

DISCUSSION

The findings of this study provide compelling evidence for the efficacy of a wearable e-textile system in enhancing motor learning for rhythmic tasks. The central hypothesis—that real-time, rhythm-synchronized haptic feedback can improve the accuracy and retention of a musically-cued motor skill—was strongly supported by the data. The significant interaction between the experimental group and the test phases demonstrates that the intervention was the primary driver of the observed improvements. Participants who received haptic feedback during their training session were not only more accurate immediately following the training, but they also retained this enhanced ability 24 hours later. This element of retention is critical, as it distinguishes true motor learning from mere temporary performance enhancement. The control group, which underwent the same training protocol without haptic feedback, exhibited only marginal improvements, likely attributable to the practice effect alone. This stark contrast underscores the unique contribution of the haptic guidance provided by the e-textile system.

The success of the system can be attributed to several factors. Firstly, the conversion of an auditory cue into a tactile one provides a multimodal learning experience. For some individuals, particularly those who are not musically inclined, translating an abstract sound into a precise physical action can be challenging. The haptic feedback serves as a direct, unambiguous signal, physically informing the body *when* to move. The significant improvement in movement consistency (i.e., the reduction in the standard deviation of timing error) for the experimental group suggests that the haptic cues helped to internalize a more stable and reliable internal rhythm. This aligns with theories of motor learning that emphasize the importance of consistent and immediate feedback in refining motor programs.

Secondly, the specific design of the e-textile system as a comfortable, integrated garment was crucial to its effectiveness. The unobtrusive nature of the technology allowed participants to move naturally without the encumbrance of wires or bulky equipment. This is a key advantage of e-textiles over other forms of haptic technology. Furthermore, the successful implementation of a computationally simple, yet effective, real-time beat detection algorithm on a low-power microcontroller is a significant technical achievement. It demonstrates the feasibility of creating intelligent, responsive garments that can operate autonomously without being tethered to external computing resources, which is essential for real-world applications in performance and rehabilitation.

While the results are promising, the limitations of this study must be acknowledged. The research focused on a very specific and simple repetitive arm movement and a single musical piece with a clear, unchanging tempo. Future research should explore the system's effectiveness with more complex choreographic sequences, varied musical genres, and dynamic tempos. Specifically, the simple, energy-based algorithm used here is susceptible to false positives from ambient noise or non-beat-related energy peaks (e.g., vocal crescendos). Its robustness in noisy environments or with music that has a less defined beat (e.g., classical or ambient music) would need to be investigated and likely improved with more sophisticated signal processing techniques. It should be noted that the 10-minute training session represents a short-term acquisition phase.

While sufficient for the simple rhythmic task in this study, complex motor skills typically require prolonged practice consolidation. However, the significant retention observed suggests that the haptic system effectively accelerated the initial stage of motor learning. Additionally, the participant pool was limited to young, healthy adults. Investigating the potential benefits of such a system for different populations, such as children learning a musical instrument, professional dancers refining their technique, or patients in neurological rehabilitation programs (e.g., Parkinson's disease) who often struggle with rhythmic movement, could reveal even more impactful applications. Additionally, a methodological limitation in the experimental design itself must be acknowledged. The Control Group wore an identical garment but without the electronic components. This means we cannot completely rule out potential confounding effects from the hardware's physical properties. The additional mass of the components (approximately 75 grams) or the simple tactile and pressure sensations of the components sewn into the garment —independent of the active haptic feedback—may have had a minor, unintended influence on the Experimental Group's performance. Future research should utilize a more rigorous 'sham' control, where the control group wears a garment with non-functional, weight-matched dummy components to fully isolate the effects of the vibrotactile feedback. The long-term effects of prolonged training with the system also remain an open question. It would be valuable to determine if continuous use leads to a dependency on the haptic feedback or if it ultimately fosters a fully independent, internalized sense of rhythm.

CONCLUSION

This study successfully designed, developed, and validated a wearable electronic textile system for music rhythm recognition and movement guidance. By integrating a computationally simple, energy-based beat detection algorithm—tuned for a specific musical track—with a network of vibrotactile actuators in a comfortable garment, we created a tool that provides direct and effective feedback *for that specific rhythmic motor task*. The experimental results demonstrated that training with this system led to statistically significant and lasting improvements in movement accuracy and consistency compared to conventional practice. Participants in the haptic feedback group not only performed better immediately after training but also retained their enhanced skills, indicating a facilitation of genuine motor learning *for this specific, low-complexity task*. This research provides a solid foundation for the application of e-textiles in performance training *for highly structured, rhythmic tasks*, offering a small but precise contribution to the field. The findings affirm the potential of haptic feedback as a powerful modality for conveying temporal information and highlight the unique advantages of e-textiles in creating seamless and effective human-computer interfaces. The focused nature of this study, with its specific task and clear data, strengthens the validity of its conclusions and paves the way for future investigations into more complex movements, diverse musical contexts, and broader user populations, ultimately aiming to bridge the gap between technology and the art of human performance.

Author Contributions

Tiantian Li designed, collected and analyzed the data, and drafted the manuscript. Tiantian Li conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Tiantian Li participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflict of Interest

The author declares no conflict of interest.

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Ethics Approval and Consent to Participate

This survey was conducted in compliance with Ethics Committee of Music College, Huanghuai University. Participants were informed of the study’s purpose and data usage prior to participation, and responses were collected anonymously. No personally identifiable information was stored.

Availability of Data and Materials

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

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Not applicable.

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