

## RESEARCH ARTICLE OPEN ACCESS

# Muscle Control of an Extra Robotic Digit

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**Received:** 9 September 2025 | **Revised:** 28 April 2026 | **Accepted:** 29 April 2026

**Keywords:** electromyography (EMG) | human augmentation | motor learning | skill transfer | supernumerary robotic limb

## ABSTRACT

Controlling an extra robotic finger requires the brain to adapt existing motor signals. While most current strategies exploit physical movement, there is growing interest in harnessing muscle activity directly via surface electromyography (EMG) as a seamless interface. Muscle- (EMG) and movement-based (force sensor) control of a Third Thumb were systematically compared. Using identical instructions and a counterbalanced within-participant design, initial skill, learning, and cognitive load were assessed across a variety of tasks, enabling a blinded comparison across control modalities. Both control modalities afforded successful Third Thumb control and learning, although force control consistently delivered better performance. Despite execution differences, learning rates and cognitive loads were comparable, with a similar evoked sense of agency. Signal analyses showed performance was predicted by real-time force sensor parameters but not by EMG, reflecting distinct control dynamics. Nonetheless, EMG training led to greater skill transfer to force control, suggesting it may better support generalizable learning. These findings demonstrate the advantages and limitations of EMG control, relative to movement control. Although EMG underperformed in overall execution, it supported enhanced generalization across control mappings and access to richer signals, highlighting the need for improved real-time decoding to fully exploit its potential.

## 1 | Introduction

Recent advances in biotechnology, robotics, and artificial intelligence have led to the rise of human augmentation technologies, aiming to enhance and expand human physical capabilities beyond their natural limitations [1, 2]. These devices take many forms, from artificial limbs or other end-effectors controlled by the biological body [3] to technologies such as exoskeletons allowing enhanced abilities [4, 5]. Beyond the motor domain, augmentation technologies may provide the user with cognitive enhancements such as smart glasses, providing tailored real-time data to a given context [6], or neurostimulation devices [7]. Augmentation technologies are not set in stone, and their potential is vast with wide-ranging applications. This versatility implies that augmentation devices can be tailored to meet the needs of diverse user groups.

Supernumerary robotic fingers (SRFs) are advanced wearable devices that augment the human hand with additional robotic digits, enabling enhanced dexterity and functionality [8]. Unlike prosthetics designed to replace lost biological function, SRFs coexist with the biological hand, therefore moving beyond replacement toward the enhancement of motor functions. While SRFs expand our physical capabilities, this extension introduces a bottleneck: the need for external control mechanisms, such as wearable sensors or neural interfaces, to operate the additional fingers without interfering with existing biological function [1, 3]. A way around this key challenge is to exploit existing motor redundancies [9].

Motor output is shaped by multiple stages of the nervous system, from high-level neural commands to muscle activation. It is therefore possible, in theory, to tap into the motor system at all stages of the sensorimotor hierarchy to produce additional

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control signals, while maintaining existing motor functions. Noninvasive approaches like electroencephalogram (EEG) and electromyography (EMG) can capture neural and muscular activity that can be then repurposed to control an augmentation device [10]. While there are multiple methods to discern muscle activity, a simple surface electrode can yield a clear signal with high signal-to-noise ratio [11], making EMG a popular choice for various controllable augmentation devices and prosthetics [12–16], as well as nonmotor augmentation technologies [17–19], and other interfaces for gesture recognition or teleoperation [20, 21]. However, to benefit from EMG for motor augmentation control, users must learn to reappropriate muscle signals intended for motor control of a specific body part to instead control a new body part [3, 22, 23]. This raises the empirical question of whether users are better able to adapt their motor plan to best support EMG control, relative to other control sensors.

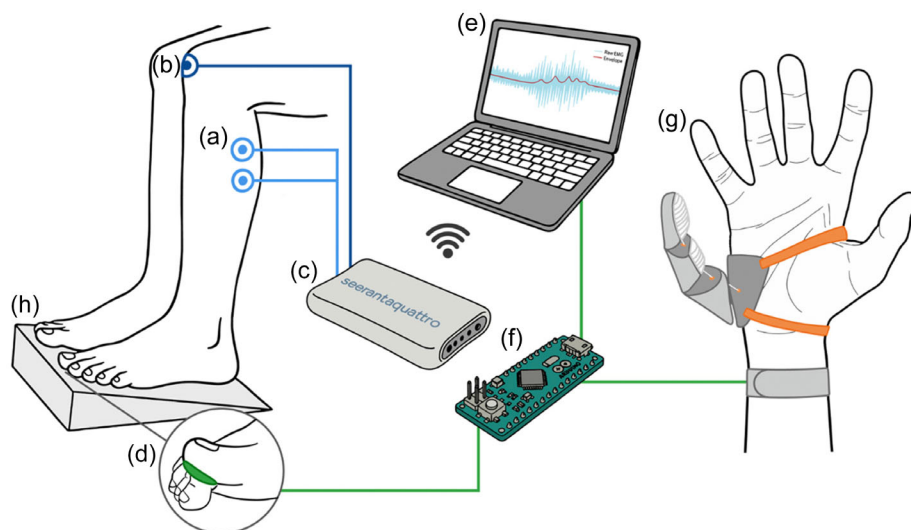
Successful control of artificial devices relies not only on generating motor commands but also on learning the mapping between those commands and their resulting sensory consequences. In motor neuroscience, such learning is commonly described as the acquisition of sensorimotor mappings, where identical movements can produce different outcomes depending on how motor signals are transformed into feedback [24]. These mappings are continuously refined through experience, enabling the nervous system to update internal control strategies based on prediction errors and sensory feedback [25]. In the context of motor augmentation, different control interfaces may therefore impose distinct sensorimotor mappings, even when driven by similar overt movements, potentially shaping both learning dynamics and generalization across control contexts.

We therefore tested the accessibility of EMG control for a SRF with an emphasis on initial skill, skill learning, generalization, and intuitive control. As a model for studying the accessibility and precision of an EMG interface, we used the robotic Third Thumb (Figure 1), created by Dani Clode Design [26]. The Third Thumb is a

three-dimensional (3D)-printed robotic thumb, designed to extend and enhance the motor abilities of an already fully functional hand (Figure 1). Originally, the Third Thumb was designed to be controlled by movement of the wearer’s toes via force sensors (FSs), providing reliable proportional control across two degrees of freedom (DoF), as limb endpoint force is an efficient way of interacting with the world [27] with high controllability [28, 29]. With the toe-controlled interface, we previously demonstrated that individuals could perform basic motor functions almost instantly [30], allowing users to achieve skilled hand-device coordination and collaboration over a short time scale [31].

In the current study, we replaced the traditional force control of the Third Thumb with EMG proportional control, also initiated by proportional toe movements. The EMG control was then put to the test by providing participants with identical instructions and experimental design, while they controlled the device using each of the two control methods in turn (see Figure 1 for technical setup). This counterbalanced design allowed us to directly compare performance between muscle and movement control across a variety of motor tasks.

In the context of motor learning, “better” control can refer to multiple outcomes, such as faster early adaptation, more stable long-term performance, or improved generalization across control contexts. When adopting a novel control strategy for an augmentation device, these outcomes may diverge. For example, a modality that supports rapid early learning might also afford more intuitive control, but also be more limited in promoting advanced skill, or generalized learning beyond the immediate training demands, and vice versa [32]. We therefore sought to clarify which aspects of learning each control interface supports best and whether EMG control could foster more transferable or generalizable skill acquisition. Rather than a single aspect of improved control, we aimed to evaluate how EMG and force control each contribute to distinct facets of learning and adaptation when mastering a *de novo* motor interface.



**FIGURE 1** | Study technical setup. (a) Bipolar electrodes placed on the gastrocnemius muscle of each leg to record the EMG signal. (b) Reference electrode to establish baseline. (c) Wireless amplifier to amplify and transmit the EMG data to the computer. (d) Force sensors (FS) used to record pressure applied by the big toes. (e) Computer to convert control signals to Third Thumb motor commands. (f) Arduino receiving the commands from the computer and actuating the servos of Third Thumb. (g) The Third Thumb (Dani Clode Design). (h) Foot stand to constrain movements and co-contraction.

## 2 | Results

### 2.1 | Behavioral Results

To compare muscle- and movement-based control, we used a within-subject counterbalanced design. The experimental design is elaborated in Figure 2A. Participants completed a test–train–test sequence with one control method and then repeated it with the other modality. Training tasks targeted different motor skills—individuated Thumb use, Thumb–finger collaboration, or Thumb–finger coordination (Figure 2B). A proportional control task assessed baseline performance and post-training gains.

### 2.2 | Movement Control Yields Better Performance, With Comparable Cognitive Load Across Modalities

We first conducted a baseline analysis to confirm that participants could effectively control the Third Thumb using both control modalities. Participants successfully completed the pretraining proportional control task with both controls, as demonstrated by a significantly positive success rate [EMG:  $t(23) = 6.803$ ,  $p < 0.001$ ; FS:  $t(23) = 11.487$ ,  $p < 0.001$ ]; however, excess force trial rates were high, indicating poor proportional control [EMG:  $t(23) = 8.756$ ,  $p < 0.001$ ; FS:  $t(23) = 6.236$ ,  $p < 0.001$ ] (Figure 3A,B).

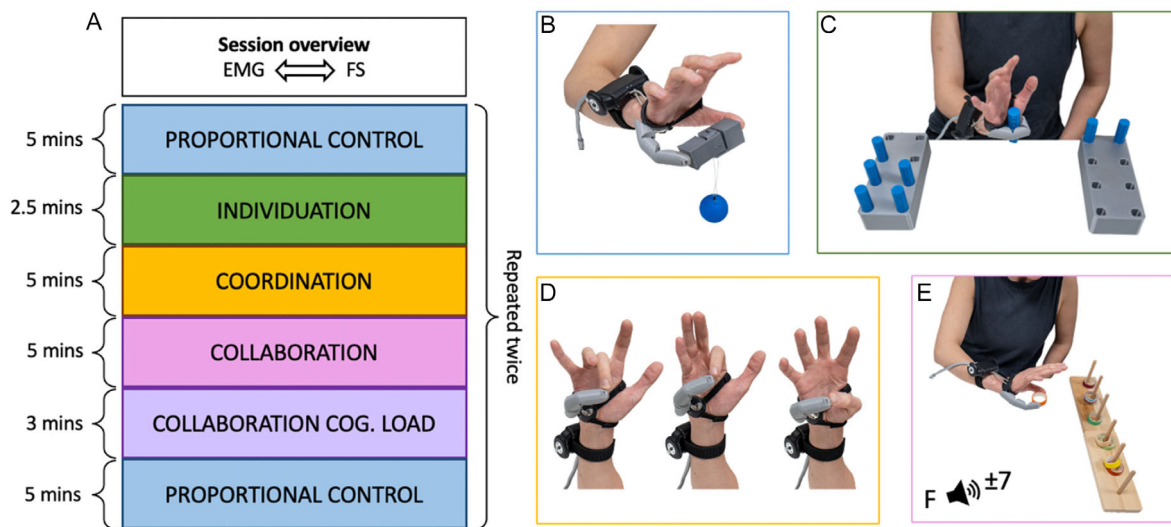
Next, we compared performance between the EMG and FS control modalities across motor training tasks (Figure 3C–E). A significant advantage for the FS control was consistently observed throughout the training phase across all tasks (individuation:

$t(23) = 4.278$ ,  $p < 0.001$ ; coordination:  $t(23) = 9.101$ ,  $p < 0.001$ ; collaboration:  $t(23) = 6.624$ ,  $p < 0.001$ ) (Figure 3C–E).

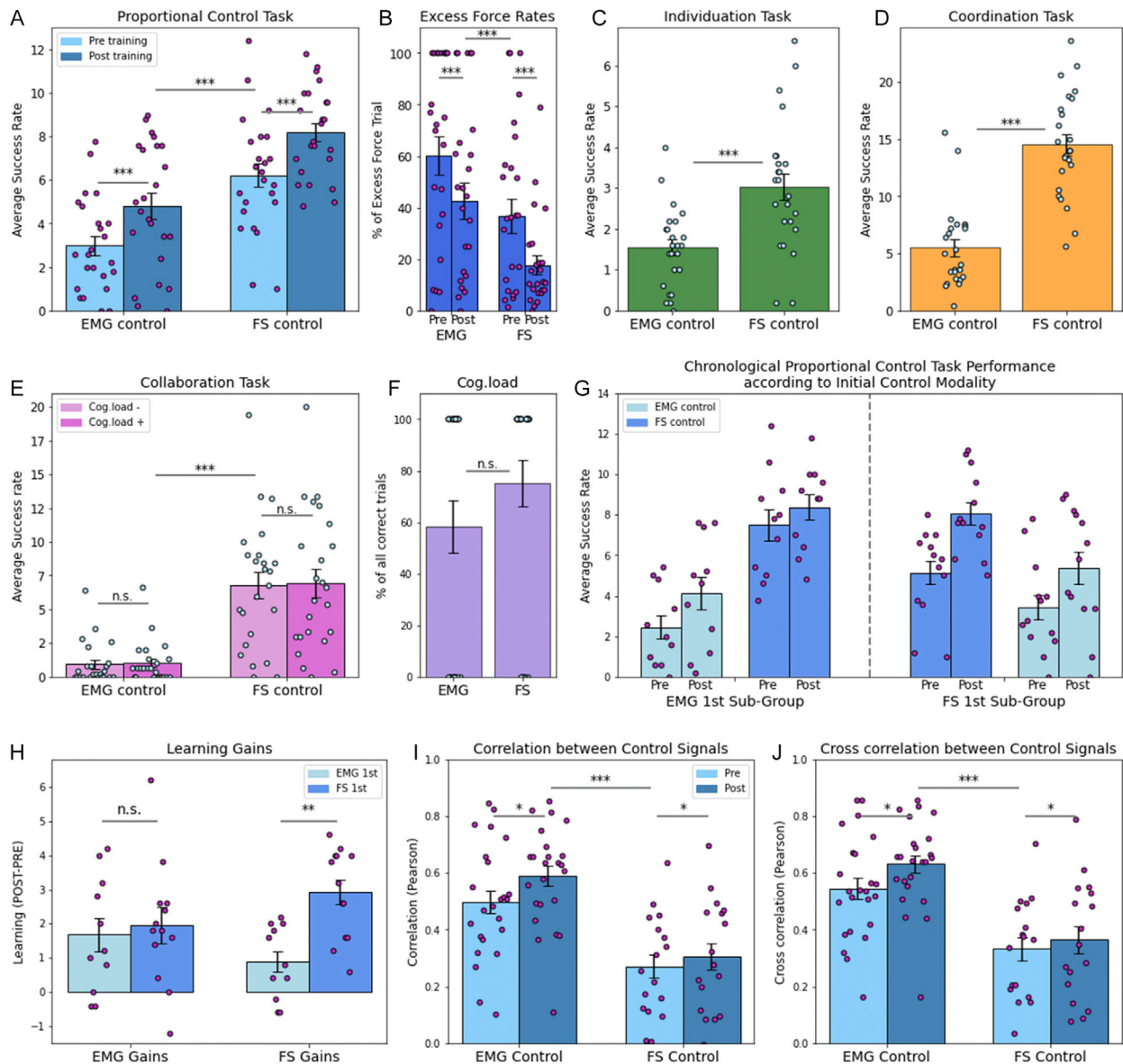
To investigate potential differences in attentional demands between control modalities, we examined the impact of additional cognitive load on motor performance. Introducing a concurrent arithmetic task during the collaboration task did not significantly affect performance for either control modalities, compared to without the cognitive load (no interaction with control:  $[F(1,23) = 0.024$ ,  $p = 0.877$ ,  $BF_{10} = 0.413$ ; post hoc tests confirmed no difference for either control, EMG  $p = 0.749$ ,  $BF_{10} = 0.284$ , FS  $p = 0.596$ ,  $BF_{10} = 0.230$ ]. Counterintuitively, for both controls, participants exhibited a slight performance improvement when cognitive load was introduced (Figure 3E), likely reflecting gains from motor task repetition, as the cognitive load task was always presented after the collaboration task. These findings suggest that neither control modality imposes substantial cognitive demands for producing Third Thumb movements. Additionally, arithmetic task performance did not significantly differ between the two control modalities ( $\chi^2(1) = 0.229$ ,  $p = 0.633$ ,  $BF_{10} = 0.562$ ; Figure 3F), further supporting the notion that their cognitive demands are comparable, although the evidence remains anecdotal.

### 2.3 | Similar Training Gains Across Control Modalities, Despite Superior Movement Control Performance

To investigate learning effects across control modalities, we examined training gains between the pre- and post-training proportional control tasks. Here, too, we found clear evidence for a superior



**FIGURE 2** | Study design. (A) Timeline for each task battery. Participants perform a series of training tasks, targeting different aspects of Third Thumb motor skill, with a proportional control task to assess training gains pre- and post-training. This battery was repeated twice for each participant (movement control and muscle control), with order of control methods counterbalanced across participants. (B) The proportional control task was repeated pre- and post-training. In this task, participants had to pick up a rectangular “fragile egg” of unstable mass (blue sphere) and transport it to a target location using the Third Thumb and biological thumb in collaboration. If too much pressure was applied, the egg would break. (C) In the Individuation training task, participants used the Third Thumb to transport pegs from one brick to another, placing the pegs into a designated slot. (D) In the coordination training task, participants used the Third Thumb to oppose the tips of their biological fingers. (E) In the collaboration training task, participants used the Third Thumb in collaboration with the biological thumb to pick up rolls of tapes and stack them over wooden pegs. (F) In the dual task, the collaboration was repeated while participants simultaneously performed an arithmetic task, which was cued by tones.



**FIGURE 3** | Behavioral task performance and relationship to control modality. (A) In the proportional control task, performed pre- and post-training for each control modality, FS control significantly outperformed EMG control, as measured using the average number of eggs moved (success rate). Performance significantly improved with training across both control modalities. (B) In the proportional control task, the percentage of trials where excess force caused the egg to break was significantly reduced during FS control, with both control modalities showing improvement following training. (C) In the individuation training task, the average number of pegs moved per minute (success rate) was significantly higher with the FS control than with the EMG control. (D) In the coordination training task, the average number of finger oppositions per minute (success rate) was significantly higher in the FS control than the EMG control. (E) In the collaboration training task, the average number of tapes moved per minute (success rate) was significantly higher for the FS control during both motor execution alone, and when there was an additional cognitive load. No deficits in performance were seen when a cognitive load was added for either control modality ( $BF_{10} = 0.295$ ). (F) During the dual task, we extracted the percentage of blocks where the participant miscalculated the arithmetic. The average percentage of incorrect blocks was not significantly different across the control modalities ( $BF_{10} = 0.670$ ). (G) In the proportional control task, learning gains were impacted by the order by which the two control modalities were performed, with participants starting with the EMG control (left) showing high pretraining performance using FS, whereas participants starting with FS control (right) show more modest EMG baseline performance relative to those starting training with EMG (left). (H) EMG training gains are similar regardless of starting control modality ( $BF_{10} = 0.383$ ), but FS training gains are significantly higher for the FS-first subgroup. (I) Correlation between the EMG and FS control signals is significantly higher when participants are utilizing EMG control, with a significant increase from pre- to post-testing sessions. (J) Cross-correlation between the EMG and FS control signals showed similar results to correlation. Bar plots represent group means, error bars show standard error of the means, and single dots show individual participants. Asterisks denote significance as follows: \* $p < 0.05$ , \*\* $p < 0.01$ , and \*\*\* $p < 0.001$ .

success rate for movement-based FS control ( $F(1,22) = 41.206$ ,  $p < 0.001$ ), which was apparent during both baseline ( $t(28.431) = 5.905$ ,  $p < 0.001$ ) and post-training ( $t(28.431) = 6.069$ ,  $p < 0.001$ ).

Superior FS performance was also demonstrated when comparing proportion of excess force trials ( $F(1,22) = 14.388$ ,  $p < 0.001$ ). Regardless of the control modality, participants exhibited a

significantly higher success rate following training ( $F(1,22)=65.385$ ,  $p<0.001$ ), with comparable training gains across both modalities (EMG:  $M=1.83$ ; FS:  $M=1.99$ ;  $t(23)=0.378$ ,  $F(1,23)=0.143$ ,  $p=0.709$ ,  $BF_{10}=0.229$ ). Correlations between pre- and post-training success rate were similar for both control methods (EMG:  $R=0.806$ ,  $p<0.001$ ; FS:  $R=0.805$ ,  $p<0.001$ ), indicating interindividual variability in performance was stable across training. Notably, at the end of the brief training session, EMG control did not achieve similar performance to FS control, reinforcing the superiority of FS in task performance.

## 2.4 | Muscle Control Is a Better Tutor for Third Thumb Motor Skill

It is well established that repeated exposure to task requirements leads to performance gains [33]. We would therefore expect participants to exhibit baseline gains when repeating the test battery in the second part of the study, regardless of the control modality. This provides a unique opportunity to examine learning transfer effects—whether movement-based training enhances muscle control and vice versa.

For each participant, we reanalyzed movement and muscle control success rates at both pre- and post-training for the proportional control task, incorporating the order in which the control modalities were introduced as a between-subject factor (Figure 3G). While the two-way interaction was not significant (control X pre/post:  $F(1,22)=0.052$ ,  $p=0.822$ ,  $BF_{10}=0.443$ ), a significant three-way interaction was observed ( $F(1,22)=4.521$ ,  $p=0.045$ ), indicating that control impacts pre-to-post learning gains, depending on the control modality used initially. This suggests that the transfer of learning between EMG and FS is asymmetrical—one control modality serves as a more effective tutor than the other. This is a potentially important observation, as it hints that control-invariant task repetition alone cannot fully explain improvements across the training batteries.

Figure 3G shows performance differences between the two subgroups of participants starting the experiment with muscle control (left; EMG training first) versus those starting training with movement control (right; FS training first). People starting the session with EMG training showed higher performance when starting the FS session (FS pre; left side), compared to those starting with FS from scratch (FS pre; right side of Figure 3G) ( $t(22)=2.374$ ,  $p=0.027$ ), whereas participants who trained with FS first and then switched to EMG (EMG-pre; right) exhibited more comparable pretraining performance with EMG to those starting with EMG training first (EMG-pre; left) ( $t(22)=1.115$ ,  $p=0.277$ ,  $BF_{10}=0.586$ ). This suggests greater generalization of learning from EMG to FS control. However, the FS learning gains from pre- to post-training is markedly lower for participants who started with EMG ( $t(22)=4.083$ ,  $p<0.001$ ; Figure 3H). This observation is likely facilitated by ceiling effects, limiting FS control learning gains from pre- to post-training as performance had already reached a high success rate following the initial EMG training (Figure 3G,H).

To further explore why muscle control is a better tutor, we correlated control signals for the main degree of freedom (flexion/extension) over time across modalities. Using both correlations

and cross-correlations (Figure 3I,J), we find that EMG and FS signals are highly correlated while participants are using the EMG output to control the Third Thumb, with significantly higher correlations than during FS control ( $F(1,16)=29.140$ ,  $p<0.001$ ). Therefore, even when using the EMG control signals, participants are expressing the FS-related toe movement, hence contributing to relevant task learning. Interestingly, this association between control modalities further grows with training, as indicated by a significant increase in correlation from pre to post-training ( $F(1,16)=5.541$ ,  $p=0.032$ ), with no interaction effect based on control order. Performing the same analysis with cross-correlation (Figure S1), to account for potential delays between the two signals, we found similar effects (control modality effect:  $F(1,16)=31.589$ ,  $p<0.001$ ; learning effect:  $F(1,16)=4.962$ ,  $p=0.041$ ). These findings provide a mechanistic insight into the high generalization capacity of EMG training.

## 2.5 | Exploratory Analysis of Control Signal Properties

Because both EMG and force signals serve as interfaces between the user and the robotic device, their structure and dynamics may influence control quality. To explore potential sources of performance variability, we extracted descriptive parameters from both signals—capturing aspects such as amplitude, smoothness, and temporal complexity—and examined whether these features could account for interindividual differences in post-training performance (see Supporting Information Results and Tables S3–S6 for full details).

A preliminary regression analysis indicated that variability in FS signal parameters accounted for a substantial proportion of behavioral variance across participants, suggesting that movement-based control quality is directly linked to measurable properties of the control signal itself. In contrast, EMG signal parameters explained little variance in task performance, consistent with the idea that the transformation from raw muscle activity to actuator command attenuates meaningful behavioral information.

We further performed an exploratory analysis using raw (unfiltered) EMG data, which suggested that several time-domain features of the unprocessed signal are more strongly related to performance, implying that some behaviorally relevant information may be lost during the filtering stage used for online control. Although these results are preliminary, they provide useful direction for future work aimed at improving EMG signal processing and mapping strategies.

While only the amplitude component was exploited for online control, EMG signals are known to carry richer information content. To dig deeper into our dataset, we also examined whether EMG-derived features could predict trial outcomes more directly using a temporal data-driven approach. Seventeen parameters (eight per channel and the interchannel correlation) were extracted using a 100 ms sliding window with a 50 ms stride and used as input to a histogram gradient-boosted classification tree. On the entire dataset, the model achieved a predictive accuracy of 66% for when a successful trial will happen and 91% for other behaviors (everything other than succeeding the task). A leave-one-participant-out cross-validation showed that EMG features predicted trial success

with an average accuracy of  $0.72 \pm 0.16$  across participants—well above chance (0.5)—demonstrating consistent mapping between EMG properties and successful control across individuals. The most informative EMG features included frequency content, zero-crossing rate, and interchannel synergies (see Supporting Information Results for full details). We note, however, that segmentation limitations (stemming from experimenter-based success marking rather than objective ground truth) likely constrained model accuracy and interpretability. Furthermore, FS signal being different in nature and content, most of the used features here are irrelevant, making this analysis unique to EMG.

## 2.6 | Greater Shared Information Between the Two DoF During EMG Control

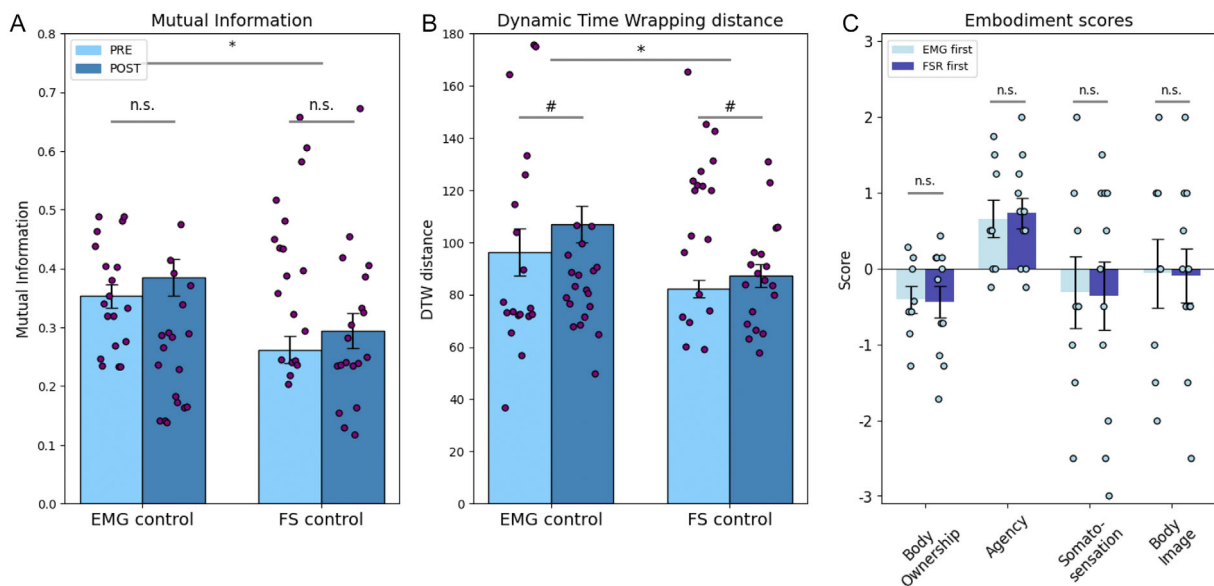
We next focused on coordination between the Third Thumb's two controllable DoFs during the proportional control task. We used distance metrics—mutual information (MI) and dynamic time warping (DTW)—to assess whether one control modality facilitated more coordinated coupling. We found significant evidence that MI was higher during EMG control ( $F(1,18) = 7.186, p = 0.015$ ) (Figure 4A). This effect suggests greater shared information between the two DoFs during EMG control. There was no significant difference in MI from pre- to post-training ( $F(1,18) = 1.893, p = 0.186, BF_{10} = 0.122$ ). Conversely, DTW distance was significantly lower for force control compared to EMG (main effect of control modality:  $F(1,18) = 5.952, p = 0.025$ ; Figure 4B), indicating more synchronized and consistent movements during force control. While MI did not significantly differ between pre- and post-training across controls, there was a trend toward increased DTW distance from pre to post ( $F(1,18) = 3.476, p = 0.079$ ). This suggests that participants increasingly adopted a sequential

activation strategy for the two DoFs following training. These findings highlight key differences between the two control methods: EMG appears to facilitate simultaneous use of the DoFs (higher MI), while FS enables more precise timing (lower DTW). However, across the experiment, the emerging strategy trended towards sequential, and presumably more accurate, movements.

## 2.7 | Both Control Modalities Induced a Sense of Agency, but Not Body Ownership

Lastly, we examined participants' subjective experience of embodiment with the Third Thumb, using four standard dimensions: agency, body ownership, somatosensation, and body image (Figure 4C). To avoid response contamination, the embodiment questionnaire was administered after the first control session. This design allowed for a between-subject comparison of control modality (muscle versus movement). Since no significant differences were found between control subgroups across any of the embodiment measures (agency:  $t(17) = 0.214, p = 0.833, BF_{10} = 0.414$ ; body ownership:  $t(17) = 0.103, p = 0.919, BF_{10} = 0.409$ ; somatosensation:  $t(17) = 0.073, p = 0.943, BF_{10} = 0.408$ ; body image:  $t(17) = 0.047, p = 0.963, BF_{10} = 0.408$ ), we report combined results below; individual subgroup statistics are reported in the Supporting Information.

Participants reported significantly positive agency scores ( $t(18) = 4.373, p < 0.001$ ), whereas body ownership scores were consistently negative ( $t(18) = 2.991, p = 0.008$ ), indicating participants perceived the robotic finger predominantly as an external object, but nevertheless perceived that they could control it. Somatosensation and body image scores were neutral



**FIGURE 4** | Coordination analysis between the two degrees of freedom (left and right leg) and embodiment scores. (A) For the proportional control task, mutual information is significantly higher during EMG control. (B) For the proportional control task, dynamic time wrapping (DTW) distance is significantly higher for EMG control, additionally there is a increasing trend from pre- to post-training. (C) Embodiment scores across the four explored categories show similar ratings across control modalities (EMG or FS first). Positive ratings, indicating perceived integration with the body, were found for sense of agency, whereas ownership was negative, indicating the Third Thumb was perceived as an external robotic device. Bar plots represent group means, error bars show standard error of the means, and single dots show individual participants. \* denotes  $p < 0.01$ , # denotes  $p < 0.08$ .

( $t(18) = 1.013$ ,  $p = 0.325$ ,  $BF_{10} = 0.373$ ;  $t(18) = 0.273$ ,  $p = 0.788$ ,  $BF_{10} = 0.246$ , respectively), reflecting neither positive nor negative interpretation of related statements.

Overall, these findings highlight agency as the only positively rated dimension, with no substantial differences between the EMG and FS control methods.

### 3 | Discussion

Our findings portray the distinct strengths and limitations of movement- (FS) and muscle-based (EMG) control, positioning movement control as a more immediately effective interface while revealing muscle control's potential role in augmenting motor learning.

Our findings demonstrate that, irrespective of the control modality, participants were able to successfully perform the motor tasks and exhibited a clear trajectory of improvement over the course of each session. This suggests that both modalities enable users to acquire and refine control over the augmentation device. Despite overall task proficiency, a consistent advantage of FS over EMG was observed across all assessed motor skills. This superiority may be attributed to the more direct and stable signal acquisition of FS, reducing variability in control and allowing for finer adjustments of movement execution. Furthermore, exploratory predictive modeling revealed that FS control parameters reliably explained performance outcomes, whereas EMG control parameters did not. Instead, EMG performance was best predicted by behavioral performance, while participants were using movement control, reinforcing the notion that muscle control introduces additional complexity. On the other hand, using EMG retroactively to successfully classify behaviors, through a range of time-window extracted features, revealed the vast range of information available within those signals. The robustness of movement control highlights the effectiveness of pressure-based control in motor tasks across the range of motor tasks tested here. Nevertheless, muscle control serves as a more effective tutor for generalization of motor control, facilitating greater improvements in subsequent FS control.

Although both control modalities originated from the same physical toe movement, the transformation between biological signal and actuator output differed substantially across conditions. Learning in this context therefore reflects adaptation to distinct sensorimotor mappings as well as progressive refinement of control strategies within each modality. Consistent with this interpretation, participants demonstrated clear improvements from pre- to post-training sessions within each control modality, indicating ongoing skill acquisition beyond initial mapping familiarization.

Despite consistently superior performance with force control, we found no significant differences in cognitive load or overall embodiment between the two control modalities. The introduction of an additional arithmetic task did not result in performance deficits. Across the embodiment dimensions, participants' perception of the Third Thumb was comparable across tasks. Together, these findings highlight that despite its lower motor performance, muscle

control does not inherently decrease the cognitive resilience or the sense of control. However, the lack of a stronger relationship between agency and control modality could be attributed to participants' limited prior experience with either modality: Without prior experience—any form of control might be sufficient to produce a positive subjective sense of agency. Regardless, given that previous studies reported increased sense of body ownership following longitudinal training to control the Third Thumb [26], prolonged experience and refinement of motor strategies may elicit a more distinct sense of embodiment in one of the two modalities.

Understanding why movement control yielded higher immediate performance helps illustrate which aspects of learning each modality best supports. Several factors contribute to the superior performance of FS over EMG. Fundamentally, pressing the toes to apply force—required for FS activation—is a more intuitive and straightforward action than selectively contracting a given muscle for EMG control. Motor learning is typically feedback-driven, as we naturally adapt movements based on interaction with the physical world [34]. The articulation of a movement against a surface provides richer and therefore more distinct haptic feedback to support motor control and learning [31]. Furthermore, FSs directly measure force application, providing a stable and proportional control signal that better aligns with the desired augmentation control paradigm of this study. In this context, the high correlation between control signals during EMG control supports that, while there are multiple ways to 'solve' FS control, there are fewer routes to learning to "solve" the EMG control challenge.

In contrast, muscles function in synergies, making it difficult and unintuitive to isolate and control a single muscle for fine motor tasks [35]. In addition, muscle activation does not inherently follow the external feedback model. As such, unintended leg movements—despite being constrained with a foot stand—could affect EMG signals more than FS signals. Then, the nature of motor unit recruitment for muscle activation further complicates EMG control [36]. Unlike movement, which is continuous and proportional, muscle engagement is discrete and occurs in step-like increments. Motor units fire in accordance with recruitment patterns [37, 38], leading to inherent variability even under constant contraction. This variability is exacerbated by the time-varying nature of EMG signals [39], which are not inherently suited for proportional amplitude recording. Even when attempting to maintain a steady muscle contraction, EMG signals can fluctuate due to physiological and electrode placement factors [40, 41], introducing unintended variations in control [42]. These considerations suggest that EMG control involves more complex and dynamic motor strategies, making it inherently more challenging to master.

Another crucial factor is signal processing. While FS signals are averaged over time and directly mapped to an output angle with minimal transformation, EMG control relies on a signal feature—amplitude—which is smoothed (from the raw EMG) and time-averaged, reducing the directness of control. Using amplitude from a single EMG channel, although intended to closely mimic the straightforward approach of FS control, may be also suboptimal due to limitation in signal filtering. This difference in signal reliability is reflected in our exploratory predictive modeling results, where FS performance could be explained

using mean force values, that is, the average amount of pressure applied was enough to explain participants' motor performance, while EMG performance was best predicted by transient features such as slope change and zero crossings—indicative of fluctuating muscle activations rather than steady control. Nevertheless, it is worth pointing that the raw EMG signal could be a rich source of task-relevant information, as demonstrated when predicting both FS and EMG performance using the raw EMG signal for off-line analysis, as well as the histogram gradient-boosted classification tree, which holds promises for exploiting EMG as a predictor of behavior.

Interestingly, because EMG is a more challenging interface to adopt when first learning to control a motor augmentation device, it might also be a more efficient tutor for generalized motor learning across modalities. Although counterintuitive, this effect aligns with existing literature suggesting that more challenging training conditions foster greater generalization across motor contexts [43]. Additionally, studies in cognitive neuroscience emphasize that learning from more variable input conditions, while slower initially, results in better and more robust generalization [44]. Thus, despite lower immediate performance, EMG training might enhance the cognitive and motor strategies necessary for effective generalization. An alternative interpretation to this greater generalization of learning is rooted in the greater correlation observed between EMG and FS signals during muscle control. When participants are operating the EMG control, they are producing task-relevant movements with their toes. This could be due to the challenges of intuitive muscle control discussed above, or due to our explicit task instructions, which emphasized movement. Either way, by exercising toe movements during EMG control, participants are implicitly training a movement strategy that will benefit their performance while switching to the new control modality. Either way, this generalization of motor learning raises the possibility that EMG training is advantageous for preparing users for varied motor control tasks and scenarios.

Several limitations in our study design must be acknowledged. Our training sessions were relatively short and learning gains were comparable between muscle and force control. With more extensive training, EMG could potentially match or even surpass FS performance, particularly as participants already showed signs of approaching ceiling levels with FS control. This aligns with evidence suggesting that while varied inputs such as EMG may result in slower initial learning, they do not inherently limit ultimate performance [44]. Additionally, our device and training paradigms were specifically tailored to FS control, potentially biasing performance outcomes in its favor. Furthermore, the hardware approach of using a single EMG channel per degree of freedom to mimic FS control likely limited EMG effectiveness; future approaches could greatly enhance EMG-based augmentation technologies by employing high-density EMG arrays, providing more reliable amplitude data. The differences between both signal's nature and therefore the slight differences between how both were processed (see "Methods") could also explain the behavioral advances observed for the force control. This uncertainty could be damped by tailoring the pipelines to be as close to each other as possible in future comparison. Finally, software improvements—such as integrating more dynamic parameters like slope changes or zero crossings or utilizing minimally

processed EMG signals—may further boost EMG's practicality and efficacy in real-world augmentation scenarios.

Beyond the laboratory, the relative advantages of EMG versus force-based control are likely to depend strongly on context. The present setup required a fixed foot position to ensure consistent contact with the FSs, an arrangement that would not be feasible in many real-life applications such as during walking, dynamic postural adjustments, or tasks performed in free space. In such situations, EMG-based control could offer clear advantages by providing stable input signals independent of mechanical contact or body posture. For example, wearable EMG arrays could maintain control reliability even when users are in motion or when environmental constraints make force application inconsistent. Thus, although EMG underperformed in our controlled seated paradigm, its flexibility and independence from contact surfaces and feedback may render it more suitable for mobile or dynamic augmentation scenarios. Future work should therefore assess EMG control performance in naturalistic, whole-body contexts to better estimate its translational potential.

## 4 | Conclusion

Our findings suggest that, while EMG-based muscle control provides access to neural signals closer to the source of movement generation, its inherent variability and complex processing pipeline make it less effective for precise proportional control compared to movement-based force sensing. Rather than evaluating which modality is universally superior, our results highlight that EMG and force control optimize different aspects of motor learning: EMG may facilitate long-term flexibility and generalization, whereas force control affords stable and accurate early performance. This multifaceted view of learning underscores that "better" control can refer to multiple outcomes. Although EMG is currently less efficient for fine proportional control, our results demonstrate that it remains a viable and promising modality for augmentative motor control, with participants successfully operating the Third Thumb using only a single bipolar electrode per degree of freedom. Addressing EMG preprocessing limitations through optimized hardware and advanced signal-processing techniques could significantly enhance EMG's practical applicability in augmentation technologies. As such, we see EMG control as a highly promising future technique for motor augmentation control.

## 5 | Methods

### 5.1 | Participants

Twenty-four healthy volunteers were recruited to participate in the study via the MRC Cognition and Brain Sciences and Department of Psychology SONA participant pools at the University of Cambridge, as well as via word of mouth. Participants were randomly allocated to the EMG control first (six females, five males; age  $M = 21.9$  ( $SD = 3.5$ )) or force control first (six females, seven males; age  $M = 25.5$  ( $SD = 8.6$ )) subgroups. All participants were right-handed and did not have any known motor disorders. Ethical approval was granted by the Cambridge Psychology

Research Ethics Committee (PREC: 2022.068). All participants were provided with an information sheet and gave their written consent before participating in the study. Eight more participants had their data collected but were excluded from analysis due to technical error or incomplete dataset. Five participants did not complete the embodiment questionnaires.

## 5.2 | Third Thumb

The Third Thumb is a 3D-printed SFR (Dani Clode Design), designed to extend and enhance the abilities of a fully functional hand [26]. The Thumb is worn over the ulnar side of the right palm, opposite the user's natural thumb (Figure 1). It is actuated by two servo motors, allowing proportional control of two independent DoF, flexion/extension and adduction/abduction. The motors are mounted on a wrist strap and in our setup powered by a wall plug (see full description in Clode et al. [30]; see Kieliba et al. [26] for description of wireless setup).

## 5.3 | Technical Setup

### 5.3.1 | Force Control Thumb

In the original Third Thumb design, control signals are generated from the user's toes using force sensing resistors (Figure 1), which vary their electrical resistance based on applied pressure. A wired communication protocol sends signals from the controlling sensors to the motors to actuate the Thumb. Signals from the right toe control the Thumb's flexion (pulling the Thumb across the hand), while signals from the left toe control adduction (pulling up toward the fingers). Thumb movements are fully proportional to the control signal, allowing the user to vary its position by modulating the force applied to the sensors.

To extract commands from the FSs, values were sampled at an effective sampling rate of 377.5 Hz. Values were normalized according to the calibration range and then appended to a buffer of 64 sample points (around 170 ms) that acted as a moving average to ensure smooth movements. Each DoF had its own buffer. The buffers average were mapped to the dynamic range of each DoF (160° for flexion and 90° for abduction). The response delay from a sensor command to a servo actuation might fluctuate around the 170 ms value according to subthreshold values in the buffers. A buffer's average close to the actuation threshold will trigger faster response than a fully empty one (Figure S4).

### 5.3.2 | Muscle Control Thumb

For the EMG setup, two bipolar electrodes were placed on the gastrocnemius muscles (medial head) of each leg (Figure 1). This muscle was chosen as it contracts when applying downwards pressure with the toes, enabling similar motor control to the movement control paradigm. An additional dry reference electrode was placed on the patella bone (knee). To reduce participants' co-contraction of agonists and antagonist muscles during EMG control, a wooden support was designed to keep the feet at an angle of 20°, also constraining variability in EMG control styles between participants.

The EMG sampling rate was 2000 Hz, with all the electrodes wired to an amplifier (Sessantotattro+, OT Bioelectronica) that sent the raw data via a WiFi connection every 100 ms to a computer (Dell 5820, Windows 10 v20H2). The raw EMG signal was first processed to extract its envelope by band-pass filtering the signal between 20 Hz and 500 Hz, band-stop filtering at 50 Hz (to remove power line noise), followed by rectification, and low-pass filtering at 2 Hz. Each DoF of the third Thumb was controlled by a moving average (400 ms) of the EMG envelope of the respective leg. A cross-correlation analysis was performed between the raw EMG (not buffered) and Third Thumb angle. It showed the highest average correlation (~0.80) for a delay of 129 ms. While this mostly relate to trend, it shows the Third Thumb was engaging according to the input within a similar delay range as when control through FSs. The average of the buffer was mapped to an angle for the Thumb actuation based on the minimum (resting level) and maximum (60% of maximum voluntary contraction) values of the calibration range.

Both control modalities offered similar Third Thumb response to either input, as shown in Figure S3.

## 5.4 | Calibration

Prior to starting the experiment, a calibration process was performed, determining a bottom and ceiling threshold, to ensure the full range of Third Thumb motion was accessible to the participant. This procedure applied mainly to the EMG part that is more subject dependant, as the Third Thumb has a default range (250–550) used during previous studies that showed great control. During the calibration procedure, participants applied maximal comfortable toe pressure for approximately 10 s. The upper bound of the control range was defined as 60% of the maximum recorded value to reduce fatigue and maintain accessible dynamic range throughout the experiment. A lower activation threshold was determined relative to baseline resting values to prevent noise-level fluctuations from generating unintended actuator responses. This participant-specific calibration ensured consistent functional control across individuals while accounting for natural differences in signal amplitude.

## 5.5 | Experimental Design

To assess performance differences between the two control methods (muscle and movement), a within-subject counterbalanced study was designed. Participants underwent a test–train–test task sequence using the first control for approximately 30 min and then switched to the second control method and repeated the test battery (Figure 2A). Both control modalities were setup at the beginning of the experiment, allowing us to blind the participant to which control they were using for a given task. Their only instruction was that pressing on the toes will actuate the Thumb proportionally. Following the first control method, participants completed an embodiment questionnaire.

The training tasks developed different motor skills, requiring either individuated use of the Third Thumb, collaboration between the Thumb and the biological fingers, or coordination

of movements between the Thumb and the fingers. Before and after these training tasks, a “testing” task focused on proportional motor control was used to determine baseline motor performance and then training gains.

## 5.6 | Testing Task

For the testing task, we used a modified version of the fragile virtual egg task (Schone et al. [43]; inspired by Clemente et al. [45]) which is designed to probe proportional control in a dexterous task (Figure 2B). The Thumb was used in collaboration with the biological thumb to pick up and transport an object (the “egg”) with unknown and unstable mass. The egg was cuboid-shaped,  $8 \times 3 \times 3$  cm in dimension with a hanging spherical weight (5g), and weighs a total of 36 g. It is called an “egg” due to its mechanical property to collapse under too much load (collapsing at 2.7 newtons, “breaking”). Participants were asked to transport the egg (placed to their right) into a basket on their left ( $25 \times 19 \times 14$  cm) as many times as they could during one block repetition (lasting one minute). Participants were instructed to transport the object without dropping it or “breaking” it. This task was repeated over five blocks, both before and after a 20-min training paradigm.

Outcome measures focus on early and late performance (pre/post-training), including average successes (average number of successful trials per block) and errors (average number of trials per block involving excessive force resulting in a “broken” egg). We also measured learning gains on these outcomes by comparing performance before and after training.

## 5.7 | Training Tasks

The training period comprised three tasks, each focused on different motor skills when operating the Third Thumb. The tasks were performed in a set order:

1. **The individuation task** (Figure 2C) was focused on motor control of the Third Thumb without support of the hand. The task consisted of eight 3D-printed cylindrical pegs ( $2.3 \times 8.3$  cm, 17 g, placed on a holder to the participants’ right) and another eight-slot peg brick holders ( $23.5 \times 10 \times 5$  cm) placed on their left. Participants were asked to move each peg to its corresponding slot on the empty brick and were given 30 s per block to move as many pegs as possible. In the event of a peg falling during transport, it was placed back to its starting position on the right. If the participant was able to slot all eight pegs before the block ended, additional pegs and a new set of brick holders were provided to continue the block. This task was performed for five block repetitions. The outcome measure was the average number of pegs successfully slotted in the brick holder across blocks.
2. **The coordination task** (Figure 2D) required a coordinated finger opposition between the Third Thumb and a biological finger, with the movements resulting in tip-to-tip contact. Starting with the biological thumb and moving sequentially around the hand to the pinky, participants

had to wait for the experimenter to confirm each trial as successful, before moving to the next finger. Once the participant reached the pinky finger, they started a new sequence beginning from the thumb. This task was performed for five blocks of one minute each. The outcome measure was the average number of finger oppositions across the five blocks.

3. **The collaboration task** (Figure 2E) involved continuous collaborative engagement of the Third Thumb and biological hand. The task consisted of rolls of tape ( $3.8 \times 1.5$  cm, 4g), placed to the participants right, and a series of six wooden poles on their left (7.5 cm apart). Participants had to grab a roll of tape using the Third Thumb in collaboration with the tip of the biological thumb, and stack it onto a pole. Participants were asked to move as many tapes as they could in a minute, and the block was repeated five times. The outcome measure was the average number of tapes moved across the five blocks.
4. **The cognitive load task** (Figure 2F) consisted of two simultaneous components. The collaboration task was repeated, and simultaneously with motor performance, participants were instructed to complete an arithmetic working memory task, designed to probe cognitive load during artificial limb motor control [26, 46, 47]. At the start of each block, a random number, between 100 and 300, was given to the participants. Participants were then presented with a series of low (100 Hz) and high (800 Hz) pitch tones randomly occurring every 5–6 s. They were required to verbally respond to each tone by adding seven following a high-pitch and subtracting seven following a low-pitch tone. Participants were instructed to prioritize correct arithmetic task performance, with the motor collaboration task being secondary in importance. This dual task was repeated for three blocks, each lasting 1 min. There were two outcome measures, the average number of tapes moved across the three blocks and the number of blocks where the participant did not answer the arithmetic task correctly.

## 5.8 | FS and EMG Parameter Extraction

To deepen our insight into the control signal parameters that best predict successful motor control of the Third Thumb, a total of eight parameters were explored off-line, covering different aspects of the FS and EMG signals: The mean reflects the overall activity level of the muscle, indicating sustained contraction strength or effort. Standard deviation measures the signal’s dispersion, indicating the extent of variability in pressure/muscle activation levels. Variability refers to the changes in signal amplitude over time, reflecting the consistency of control/muscle contractions. Fractal dimension assesses the complexity of the control signal, providing insights into the intricate patterns of muscle activation. The first derivative variance captures the rate of change in the signal, highlighting the speed and smoothness of control signals. The second derivative variance measures the acceleration or deceleration in these changes, offering deeper insights into the dynamics of control and coordination. The slope change reflects the dynamics of signal variations and can indicate abrupt changes or events in control activity. Waveform length is the cumulative sum of the absolute differences between

consecutive control signal sample points, often used to assess muscle fatigue or effort.

Five additional parameters were investigated for only the raw EMG signal: Frequency content involves the analysis of the signal's spectral components, revealing the different frequencies at which muscles are active, which can be linked to different types of muscle fiber recruitment. The zero-crossing rate is the number of times the EMG signal crosses the zero-amplitude line within a time window (here one second), providing further insight into signal complexity in muscle activation patterns. The wavelet energy (complex Morlet wavelets were used for analysis) is the total energy of the EMG signal within specific frequency bands (here all frequencies present in the signal), obtained using a wavelet transform, highlighting localized energy patterns in time and frequency. Band energy is the same analysis targeted solely to the EMG frequency range (20 to 150 Hz). Wavelet entropy is a measure of the disorder or randomness in the wavelet coefficients of the EMG signal, capturing signal complexity and irregularity, often used to differentiate between voluntary and involuntary muscle activity. The FS signal being strictly positive (as the rectified EMG signal) meant there was no need to look at zero crossings, and EMG specific parameters such as the wavelet energy or entropy that are not relevant for the FS signal.

When computing the FS/EMG parameters, the FS/EMG time series for each block of the proportional control task were extracted, and all the parameters were then computed through a Python script. Parameters were averaged over block repetitions, resulting in one value per parameter for a given task. To minimize multiple comparisons, all candidate parameters were first correlated with each other. Similarity profiles were determined by how highly a parameter correlated with all the others (Tables S1 and S2). Parameter with similar profiles were eliminated, isolating five unique signal characteristics that were used for statistical analysis (standard deviation, mean, zero-crossing rate, second derivative variance, and fractal dimension).

Similarly, for the histogram gradient-boosted classification tree training, the EMG time series (from each block of a task) of each channel were truncated into 100 ms time windows (with 50 ms overlap). For each subwindow, eight parameters were computed (introduced above except derivative's variances and wavelet entropy) as well as the correlation between both channels. The resulting feature time series were fed to the model leaving one participant out each time, allowing to assess its performance on unseen data.

## 5.9 | Coordination Parameters

To analyze coordination between the two DoFs, MI and dynamic time wrapping (DTW) distance between the two DoFs were computed. MI is a method that captures both linear and nonlinear dependencies between the two input signals. If the MI is high, it suggests that there is a strong interaction or relationship between the two inputs, indicating synchronized coordination. DTW is a technique used to compare the similarity between two time series, even if they are not perfectly aligned in time. This can be useful if participants coordinate the two DoFs but with slight timing discrepancies (e.g., one DoF slightly lags

behind the other). Extraction of the coordination parameters was done the same way as for the FS and EMG control signal parameters.

## 5.10 | Embodiment Questionnaire

To assess participants' phenomenological experience with the Third Thumb, participants were asked to complete an embodiment questionnaire after the train-test battery with the first control. Participants were asked to rate their agreement with 20 statements (adapted from Kieliba et al. [26]; inspired by Longo et al. [48]) on a seven-point Likert-type scale ranging from -3 (strongly disagree) to +3 (strongly agree). Four statements were "catch" statements, designed to confirm the participant was paying attention to their ratings. The other statements were clustered into four main categories, probing different aspects of embodiment, namely, body ownership, agency, body image, and somatosensation. For each participant, questionnaire scores were averaged within each embodiment category. Note that we did not repeat the questionnaire after the second control strategy, to avoid response contamination.

## 5.11 | Statistical Analysis

Data was processed using python (version 3.1713), edited in Visual Studio (VS) Code (version 1.87.2). All statistical analysis were performed in JASP (version 0.18.3) or using Python, edited in VSCode. All data was inspected for violations of the normality assumption by the Shapiro-Wilk test, and outliers were removed at a threshold of  $\pm 3$  SD. An alpha level of 0.05 was used throughout, and any nonsignificant results of interest were followed up with a corresponding Bayesian test (Cauchy prior width  $r = 0.707$ ). Bayes factors were interpreted using  $BF < 1/3$  as sufficient evidence in support of the null hypothesis,  $BF > 3$  as sufficient evidence in support of the alternative hypothesis, and  $1/3 < BF < 3$  as inconclusive evidence [49].

When making pairwise comparisons of performance in the training tasks between the two control conditions, a Student's paired sample t-test was used. A repeated measures (RM) ANOVA was also used to assess performance in the dual task, with factors of control method and task version (collaboration or dual task). A chi-square test was used to then further explore the proportion of trials in the dual task that had incorrect answers. An RM ANOVA was used for the pre-post-testing task outcomes to compare training gains in each control condition, with a mixed ANOVA also used when considering control order. This was run separately for success rate and percentage of trials with excess force. Similarly, an RM ANOVA was used to compare correlation values between the control signals. Pearson's correlation was used to correlate signal parameters with performance. Paired sample t-tests were used to compare gains in the proportional control task with the two control modalities. To explore which EMG or FSR features explain behavioral performance, we ran exploratory backward stepwise regressions (entry: 0.05; removal: 0.1).

To see if participants were neutral or experienced positive/negative embodiment toward the Thumb, a one-sample t-test was

used for each subgroup to see if the scores in each category were different from zero. An independent sample t-test was then used to compare the subgroups.

## Acknowledgments

The study was funded by UKRI's Frontier Research Guarantee (EP/X040372/1), the Engineering and Physical Sciences Research Council (EP/W004062/1), and the Medical Research Council (MC\_uu\_00030/10). T.R.M. was partially funded by a Wellcome Trust Senior Research Fellowship (215575/Z/19/Z). We acknowledge support from Meta through a charitable gift. We thank our participants for their valuable help. We thank Clara Gallay for data collection. We thank Mario Bracklein (CTRL-labs at Reality Labs) for helpful insight on the manuscript. For the purpose of open access, the authors have applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising from this submission.

## Funding

This study was supported by UK Research and Innovation (EP/X040372/1), the Medical Research Council (MC\_uu\_00030/10), the Engineering and Physical Sciences Research Council (EP/W004062/1), and the Wellcome Trust (215575/Z/19/Z).

## Ethics Statement

Ethical approval was granted by the Cambridge Psychology Research Ethics Committee (PREC: 2022.068). All participants were provided with an information sheet and gave their written consent before participating in the study.

## Conflicts of Interest

The authors declare no conflicts of interest.

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## Supporting Information

Additional supporting information can be found online in the Supporting Information section.