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Citation (APA)
Garzás-Villar, A., Riera-Cardona, A., Derumigny, A., Micah Prendergast, J., Cramm, J. M., & Marchal-Crespo, L. (2026). Manipulating Tangible Virtual Object Dynamics to Promote Learning of Precision Force Generation. *IEEE Access*, *14*, 161691-161711. https://doi.org/10.1109/ACCESS.2026.3743799

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Received 11 September 2026, accepted 7 October 2026, date of publication 14 October 2026, date of current version 23 October 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3743799

RESEARCH ARTICLE

Manipulating Tangible Virtual Object Dynamics to Promote Learning of Precision Force Generation

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This work was supported in part by the Convergence Human Mobility Center, a Flagship Initiative funded by the Convergence Alliance (Technische Universiteit (TU) Delft, Erasmus Medical Center (MC), Erasmus University Rotterdam) under Grant 2022036; and in part by the Dutch Research Council (NWO, Vidi) under Grant 18934.

This work involved human subjects in its research. Approval of all ethical and experimental procedures and protocols was granted by the TU Delft Human Research Ethics Committee (HREC).

ABSTRACT Robotic haptic devices combined with virtual reality offer novel opportunities to train fine force generation, an essential yet overlooked component of post-stroke rehabilitation. This study proposes that manipulating the dynamics of tangible virtual objects can be leveraged to train precise force control while engaging the somatosensory system. We conducted an experiment with fifty healthy participants who performed a curling-inspired task in which they stretched a virtual spring to generate a target release force to propel the stone to a predefined location. During training, the spring's force–elongation relationship was modeled as either a linear or non-linear function, i.e., a Gaussian or antisymmetric Gaussian (AS-Gaussian) function with zero derivative at the release target force. Results indicate that the AS-Gaussian group consistently achieved higher force accuracy during training than the linear group, while the Gaussian group only outperformed the linear group toward the end of training. Analysis of personality traits revealed that higher Free Spirit scores were associated with poorer performance and reduced task exploration under Gaussian dynamics, whereas higher Transform-of-Challenge scores correlated with increased exploration. Despite these training effects, no significant differences in motor learning were found across spring types or personality traits. Participants primarily relied on learned target elongation rather than target force, as evidenced by performance in a transfer task with a different stiffness but the same target force. While promising for sensory training, our findings highlight limitations that should be addressed before application in neurological populations, especially the reliance on positional cues and arm fatigue, among others.

INDEX TERMS Motor learning, personalization, precision force, robot-assisted rehabilitation.

I. INTRODUCTION

Stroke affects around 12 million people yearly worldwide and remains a leading cause of long-term disability [1]. Somatosensory deficits occur in up to 89% of stroke survivors [2], compromising the integration of proprioceptive and tactile information, which are essential to regulate force generation and control [3]. This decline leads to reduced force precision, increased variability, and impacts everyday actions such as grasping, lifting, or manipulating objects [4], [5].

Most neurorehabilitation interventions, however, primarily target motor restoration while the somatosensory component, especially somatosensory-guided force control, is generally overlooked [6], [7]. The most common approach involves somatosensory stimulation—through electrical [8], [9], [10], magnetic [11], [12], or mechanical methods [13]—to

The associate editor coordinating the review of this manuscript and approving it for publication was Tommaso Lisini Baldi.

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augment sensory processing. Yet, this *passive* stimulation limits patients' active engagement and, therefore, may restrict opportunities for sensorimotor integration and error-driven motor learning [14]. To overcome this limitation, feedback-based training using visual [15], [16] or auditory [17] feedback has been proposed to, e.g., support grip force regulation [18]. Yet, reliance on this feedback may reduce the engagement of the somatosensory system, as visual or auditory information alone is often sufficient to perform the task. To our knowledge, the use of somatosensory information to support force control training has mainly targeted the coordination of muscle synergies [19], [20], whereas its use to train fine force control for arm-object interaction remains under-studied.

We propose leveraging robots to actively engage patients somatosensory systems during force control training. Studies have demonstrated that adaptation to new task dynamics can be accelerated by temporarily modifying those dynamics. For example, the learning rate of walking in a viscous force field could be accelerated when amplifying the force fields during the initial steps, prompting a larger adjustment in muscle commands [21]. Studies on force fields in upper-limb tasks [22], [23], [24] further support the idea that temporally modifying task dynamics can provide participants with an enriched sensorimotor experience that challenges the motor system [25]. Although promising, previous work focused on manipulating the dynamics of meaningless artificial tasks, e.g., moving in viscous fields, which are far from the force-precision skills needed to perform activities of daily living.

Modulating the rendered dynamics of virtual objects might be a more meaningful way to shape how users generate, regulate, and learn to produce human-object interaction forces. Advanced robotic devices allow precise simulation of interaction forces with tangible virtual objects, known as haptic rendering, and enable programmable, repeatable training environments that cannot be achieved in conventional training [26], [27]. Importantly, haptic rendering enables somatosensory engagement in ways that closely mimic natural object manipulation [28] and support the development of internal models similar to those used in real-world object handling [29].

As a proof of concept, we present a system with the potential to train fine force generation and show the first results from an experiment with fifty unimpaired participants. Our system manipulates the linearity of the force-elongation relationship of a virtual spring into a Gaussian or antisymmetric Gaussian relationship with zero derivative at the point of correct force generation. By doing so, we aim to train—through two different mechanisms—fine force generation leveraging somatosensory feedback without relying on visual or auditory cues. The Gaussian profile introduces a salient deviation from linear dynamics by reducing force beyond the target force, which is expected to promote exploratory behavior and, therefore, movement variability, known to support motor learning [30], [31]. In contrast, the antisymmetric Gaussian profile provides a localized increase in resistance beyond the target, resembling haptic guidance strategies that constrain movement around the desired action, leveraging the exploitation of successful actions as a learning mechanism [19], [32].

We expect that trainees with different personality traits might benefit differently from the proposed modified dynamics. In recent work [33], [34], we found that participants with more goal-oriented traits—i.e., autotelic behaviors [35] or gaming styles based on achieving goals [36]—tended to perform worse when training to perform a dynamic task with the support of robotic haptic guidance—i.e., physical guidance through the desired movement—likely because they perceived the guidance as interfering with their task success. Conversely, those participants who exhibited traits more closely related to exploratory behaviors performed worse without guidance, as they probably prioritized exploring the robot behavior over achieving high performance. We also found that participants' Locus of Control—the extent to which individuals attribute outcomes to their own actions versus external factors [37]—influenced how they physically interacted with the robot.

In view of these findings, we designed a study to: (1) investigate motor learning of fine force generation under our ''surreal'' haptic rendering-based approach, and (2) determine how individual psychological traits influence users interaction with such haptic rendering. As a necessary step prior to clinical translation, we first evaluated our approach in fifty healthy participants with no history of neurological disorders, allowing us to refine the study design, characterize system performance under controlled conditions, and limit inter-individual variability associated with stroke recovery [38]. Participants performed a virtual curling-style task using a haptic delta device. They were asked to propel a virtual stone across a sliding sheet of ice to reach a defined target position ahead of them. To propel the stone, they had to pull with their arm against a virtual spring rendered by the delta device, and upon release, the stone slid a distance proportional to the force generated by the spring at release. The task is thereby inherently force-based: success depended on selecting and producing the appropriate pulling force at stone release. During training, participants were assigned to one of three groups that experienced different spring dynamics: a standard linear force-elongation relationship, an antisymmetric (AS-) Gaussian, or a Gaussian relationship.

Task performance was quantified as the absolute difference between the target force and force at release and, when using a non-linear spring, the absolute difference between the desired and actual spring elongation at release. We also investigated participants' exploration behavior across the three different virtual springs by comparing the distance the stone traveled before release and the smoothness of its movements. Motor learning was assessed as performance improvements from

baseline to short- and long-term retention tests under the standard linear dynamics. To infer whether motor learning relied primarily on force-based information rather than proprioceptive cues, we tested participants' performance in a transfer task that required playing with a linear spring with higher stiffness. We also evaluated the influence of personal characteristics on motor performance during training and motor learning.

We formulated the following hypotheses:

H1 Participant's performance during training will be influenced by the training condition and personality.

H1.1 Stiffness profiles that deviate more from the linear spring would increase awareness of the target force and thus promote greater performance gains along training (Gaussian > AS-Gaussian > Linear).

H1.2 Participants with high goal-oriented characteristics and those reporting higher perceived control over their movements, will show greater performance gains when training with the Linear or AS-Gaussian springs compared with average participants, as they would perceive less "guidance", in line with [34].

H2 Exploratory behavior during training will be influenced by the training condition.

H2.1 Exploration will decrease over the course of training, irrespective of group assignment.

H2.2 Training conditions that promote larger performance gains in H1.1 will also elicit higher exploration behavior at the beginning of the training.

H2.3 The pronounced deviation of the Gaussian w.r.t. the linear spring is expected to particularly encourage exploration in individuals motivated by novelty and open-ended interaction.

H3 Participants will learn the task differently depending on the training condition and personality.

H3.1 Performance will improve from baseline to short- and long-term retention, regardless of the training condition.

H3.2 Performance improvements from baseline to retention will differ across training conditions, reflecting the strategy-dependent differences observed during training (as hypothesized in H1.1).

H3.3 Personality traits associated with improved performance (H1.2) or increased exploration (H2.3) during training will be associated with greater performance gains after training compared to average participants.

H4 During the transfer task, participants will rely primarily on force perception rather than proprioceptive information. This will lead to a systematic positional offset w.r.t. the "trained" target spring elongation.

II. METHODS

A. EXPERIMENTAL SETUP

The experimental setup consisted of a *Delta*.3 haptic device (Force Dimension, Switzerland) and a computer screen to display the game (Fig. 1). The haptic device provides three translational degrees of freedom at its end-effector and can render forces up to 20 N along each of the three translational axes. The robot control was implemented in C++. Rendering and data recording were performed at 1 kHz. Participants interacted with the device via a ball-shaped end-effector equipped with a button.

Both the haptic device and the monitor were positioned on a table, whose height was adjusted so that participants could perform the task while standing in a relaxed posture with the elbow flexed at approximately 90°. For right-handed participants, the monitor was placed on the left and the haptic device on the right, each elevated on dedicated platforms to ensure a comfortable working height. For left-handed participants, the setup was mirrored along the z-axis (Fig. 1).

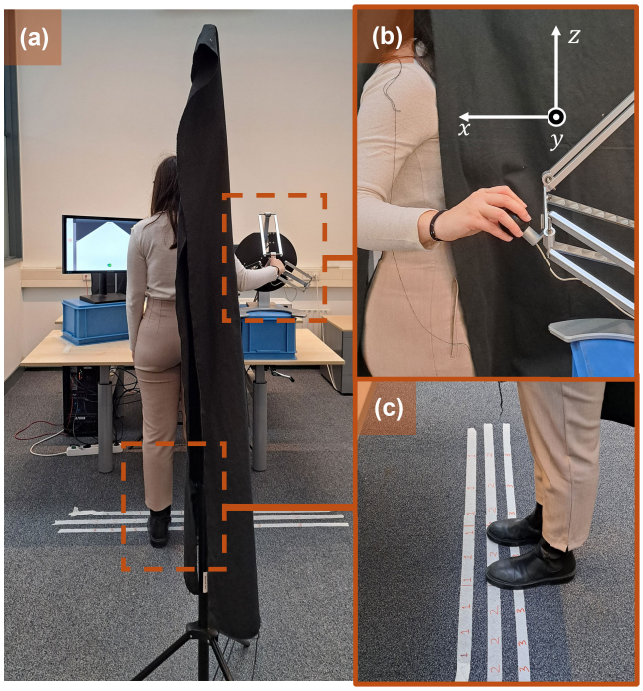


FIGURE 1. (a) The experimental setup consists of a *Delta.3* haptic device (Force Dimension, Switzerland) together with a computer screen. (b) Holding position of the device end-effector and reference frame. (c) The three predefined feet positions.

To reduce the influence of visual cues on participants' performance, a curtain was positioned across the participant's shoulder, occluding the device as well as their arm and hand. To also reduce the influence of proprioceptive information, we continuously adjusted their position w.r.t. to the robot along the x-axis. To do so, we systematically relocate them along three predefined foot-placement references, marked by white stripes on the floor (Fig. 1c). Each stripe was 4 cm wide and separated by 3 cm.

B. THE CURLING-LIKE TASK

The force-dependent task was implemented as a virtual curling-style game in Unity3D, version 2022.3.37f1. The virtual environment consisted of a white horizontal surface

representing the ice sheet and a blue cube positioned in front of the participant representing the curling stone (Fig. 2). At the far end of the surface, a target board—red concentric rings—was shown. The goal was to propel the cube using the robot end-effector so that it slid across the surface and stopped as close as possible to the center of the target. On the left side of the screen, a top-down view of the entire surface was displayed to facilitate the visualization of the "shot" outcome.

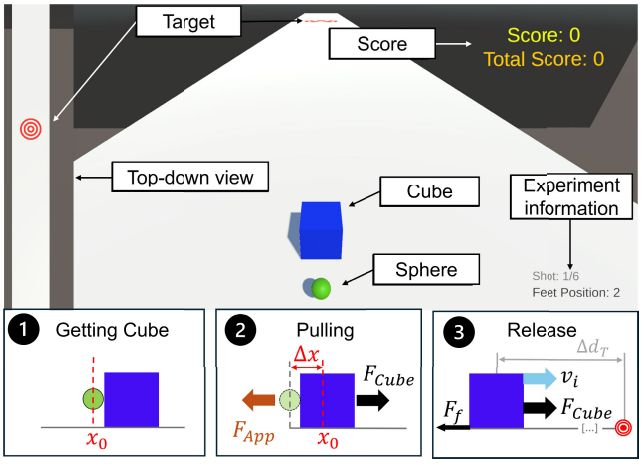


FIGURE 2. ***Up*: Screenshot of the game. *Down*: Representation of the different phases of the cube release. x_0: Initial grabbing point, Δx: Spring elongation, F_{App}: Force applied by the participant, F_{Cube}: Force generated by the virtual spring, F_f: Friction force, v_i: Cube velocity at time i, Δd_T: Distance from the cube to the target's center.**

The overall workflow of the task is illustrated in Fig. 2. Participants moved a green sphere in the game that moved proportionally to the robot end-effector (100 cm in Unity: 1 cm robot coordinates). The robot end-effector motion was constrained to translate along the x-axis, while two stiff proportional controllers ($k = 7$ N/m) prevented movements along the other two axes. To "grab" the virtual cube, participants moved the green sphere until it contacted the cube, then pressed the button on top of the end-effector. Once grabbed, both the sphere and the cube disappeared, eliminating visual cues. Participants then pulled the end-effector towards them along the robot's x-axis while holding the button pressed. During this movement, the device rendered the force corresponding to the active spring (see Section II-C). The cube reappeared and was propelled as soon as the button was released. At this point, the force experienced by the participant through the device was transmitted to the cube, which in turn slid a distance Δd_T on the surface according to the following equation of movement:

$$F_{Cube} = \frac{m}{UT}\sqrt{2\mu g \Delta d_T}, \tag{1}$$

where $m = 1$ Kg is the cubes mass, $g = 9.8\,\text{m/s}^2$ the gravitational acceleration, $\mu = 0.02$ the static/dynamic friction coefficient, and UT is the Unity frame update time (0.02 s).

The center of the target was located 500 m from the initial blue block position, with a radius of 29 m. The scoring system for the six rings, from the innermost to the outermost, was: 100, 20, 10, 5, 2, and 1 points. Two scores were displayed on the top-right corner of the screen (Fig. 2). The *Score* reflected the points accumulated within the current trial (see Section II-E) and was reset at the beginning of each trial, whereas the *Total Score* displayed the cumulative points across the entire experiment. Because of the cube's long travel distance after release, its motion was accelerated by a factor of 20. Once the cube came to rest due to friction, the points were displayed for 3 s. The cube then briefly disappeared, only to reappear at the same initial position.

C. HAPTIC RENDERING OF THE VIRTUAL SPRINGS

The cube was propelled by transferring the force generated by pulling virtual springs. A standard linear spring was used by the *Control* group during training and by all participants in trials not related to training (see Section II-E). We also defined two non-linear springs to promote learning of the target force that makes the cube reach the center of the target on the floor (Fig. 3). All virtual springs were designed to reach a target force of $F_T = 10$ N, corresponding to a target spring elongation Δx_T of either 90 mm (main task), or 70 mm (transfer task), calculated as the distance between the release point and the initial grabbing point along the robot x-axis.

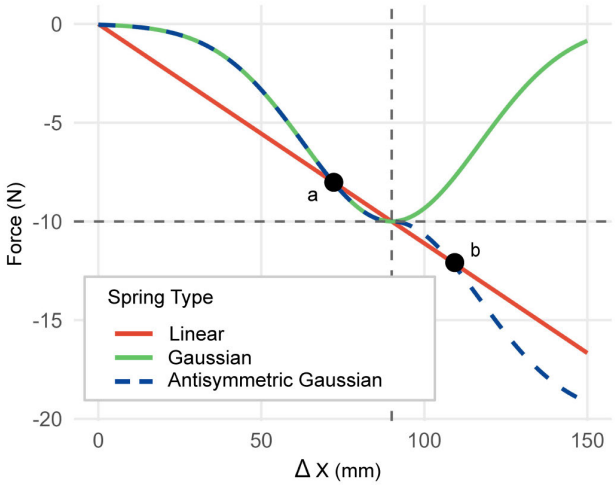


FIGURE 3. **Force-elongation relationship for the different virtual springs. The points a and b indicate the intersections between the Antisymmetric Gaussian and the Linear springs.**

1) LINEAR SPRING (LS)

The LS followed a classical spring equation:

$$F_{LS} = k_{LS}\Delta x, \quad \text{where} \quad k_{LS} = \frac{F_T}{\Delta x_T}. \tag{2}$$

The force F_{LS} rendered to the participant through the robot end-effector (corresponding to F_{Cube} in Eq. (1)), depends on the cube position w.r.t. the cube's initial grabbing position

(Δx). The stiffness of the LS, k_{LS}, is constant and depends on the target force F_T and target elongation Δx_T in the corresponding experimental phase.

2) GAUSSIAN SPRING (GS)

The GS implemented a Gaussian force–elongation relationship with a zero-derivative at the target force. This modification w.r.t. the LS was intended to ''cue'' the target force needed to hit the target center. It was designed to be clearly noticeable and promote active participants' exploration of the spring dynamics. The force-elongation Gaussian relationship followed the equation:

$$F_{GS} = F_T \cdot \exp\left(-\frac{(\Delta x - \Delta x_T)^2}{2W^2}\right), \tag{3}$$

where W is the width of the Gaussian envelope, set to 27 mm (in robot end-effector frame). Note that when the end-effector was pulled beyond the curves peak at the target force, the rendered force decreased. The value of W was empirically chosen based on the available robot workspace (400 × 400 x 260 mm). Preliminary testing indicated that smaller W values produced an overly abrupt transition after the target force, whereas larger values broadened the Gaussian peak and reduced the spatial localization of the target force/elongation. Moreover, larger W values made the Anti-symmetric Gaussian spring increasingly similar to the LS. The same value of W was therefore used for both nonlinear springs.

3) ANTI-SYMMETRIC GAUSSIAN SPRING (AGS)

The AGS implemented a nonlinear force–elongation relationship that, in comparison with the GS, introduced a more subtle variation w.r.t. the LS. In particular, the relationship evolved following an anti-symmetric Gaussian curve, with the zero-derivative point centered on the target force with the same width W as the GS.

$$F_{AGS} = \begin{cases} F_T \cdot \exp\left(-\dfrac{(\Delta x - \Delta x_T)^2}{2W^2}\right), & \text{if } \Delta x < \Delta x_T, \\ -F_T \cdot \exp\left(-\dfrac{(\Delta x - \Delta x_T)^2}{2W^2}\right) + 2F_T, & \text{if } \Delta x \geq \Delta x_T. \end{cases} \tag{4}$$

This formulation yielded a force profile with increasing force as the spring elongated, then transitioning to a brief plateau around the target force. Once the plateau was overcome, the force increased steeper than the LS, producing the perceptual effect of a ''subtle wall.''

D. PARTICIPANTS

A total of 53 participants completed the experiment, but only 50 could be included in the analysis. Among the three excluded participants, one did not sign the informed consent, one failed to complete a required questionnaire, and one presented corrupted data. Of these 50 included participants, 17 identified as female, 33 as male, and none as non-binary. The mean age was 26.3 ± 3.74 yo. Handedness was assessed via questionnaire (two left-handed participants). The final group allocation consisted of 17 participants in the Linear condition, 16 in the Gaussian condition, and 17 in the AS-Gaussian condition. All participants provided written informed consent prior to participation.

E. STUDY PROTOCOL

The experiment was conducted at Delft University of Technology, Delft, the Netherlands, and was organized into two sessions, scheduled 1–4 days apart to evaluate long-term retention [27]. Only two participants were scheduled more than four days later, due to personal circumstances. An overview of the experimental protocol is provided in Fig. 4.

Prior to the first session, participants completed an online battery of personality trait questionnaires (Section II-F). The remaining data were collected in two separate data collection periods, conducted three months apart, with 30 and 23 participants tested in each period. In both periods, the first half of participants was randomly assigned to each of the three experimental groups, whereas the second half was allocated based on their scores in the Locus of Control Questionnaire (Section II-F) to balance this trait across experimental groups. This pseudo-allocation was implemented based on our previous findings [33], as Locus of Control could influence how participants react to the potential guiding effects of the different virtual springs, potentially affecting learning. We also tracked the distributions of the remaining personality traits and Hexad gaming styles during allocation to ensure that low, medium, and high scores for each variable were represented in all three experimental groups. The distributions of these variables across the experimental groups are reported in the Appendix A.

The first experimental session (Day 1) began with a five-minute presentation about the curling-like task. Participants were informed that the force felt during cube release would determine its displacement, but were not made aware of the different spring conditions. Participants were also instructed on how to hold the robot end-effector and to press the button using their index finger to reduce variations between participants. Participants were then positioned in the experimental setup. The height of the table was adjusted, and they were asked to place their feet 7 cm from the table, i.e., align with the second white strip on the floor. Once the participants were ready, a familiarization phase began. They completed four practice shots with the LS. Each shot consisted of the entire sequence: the cube appearing, grabbing it, releasing it, and waiting until it stopped, allowing participants to understand the game mechanics. No target board was displayed during these familiarization shots.

After the familiarization phase, the main experiment started with a first Baseline phase to evaluate participants' initial skills. During Baseline, they first completed two trials of six shots each with the standard LS (referred to as the *main task*), with no breaks between trials. They then completed a first round of questionnaires, which included items from

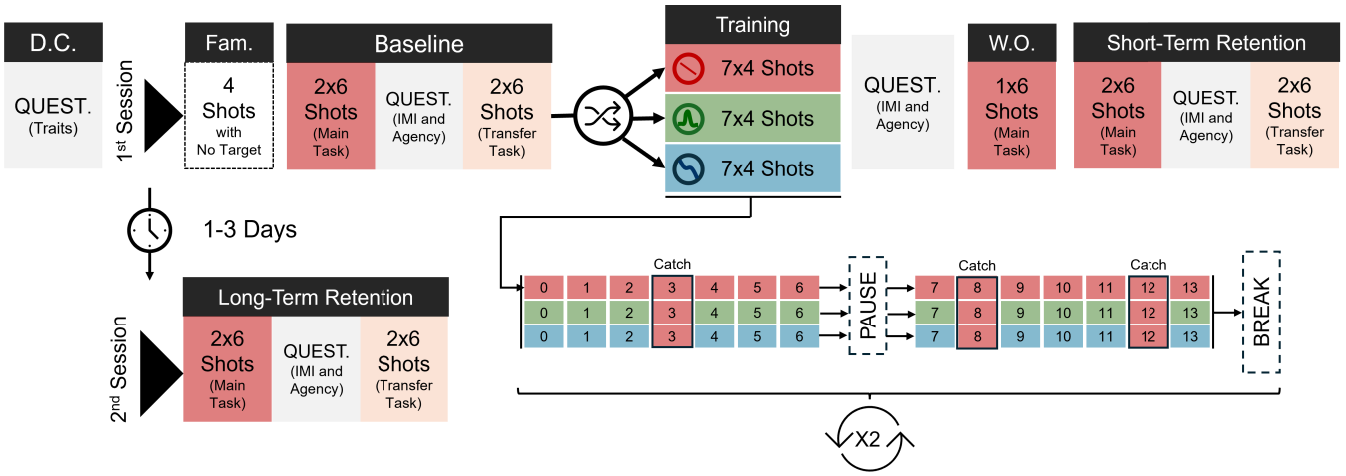


FIGURE 4. The study protocol included two sessions spaced by 1 to 4 days. A trial comprised 6 shots during the retention phase and 4 during the training phase. D.C.: Data collection, Quest.: Questionnaires, W.O.: Wash out.

the Intrinsic Motivation Inventory and an adapted version of the Agency Questionnaire from Piryankova et al. [39]. Given the focus, amount, and complexity of the present hypotheses, we considered the analysis of these questionnaires out of scope. Participants then performed a Baseline Transfer phase, consisting of two trials of six shots each. In this phase, participants interacted with the transfer spring, an LS with a higher stiffness that shifted the target elongation from 90 mm to 70 mm, while the target force was held constant. The *transfer task* was incorporated to evaluate whether participants would learn the target force or the target spring elongation.

After Baseline, participants were invited to take a break before starting the Training phase. The Training consisted of four blocks of seven trials each, with each trial comprising four shots. During this phase, the rendered spring was either LS, GS, or AGS, depending on the experimental group each participant was allocated to. After each trial, a message was displayed instructing participants to change their foot placement to a different white strip on the floor to prevent their reliance on proprioception while performing the task (Fig. 1). The sequence of foot positions (i.e., position 1, 2, and 3) was randomized but kept consistent across participants. To discourage reliance on the training-specific spring, we included a catch trial every 4-5 trials (Fig. 4) in which the LS was rendered regardless of group allocation. Participants were offered optional breaks between blocks. Only the 2-minute break between the second and third block was mandatory to limit shoulder fatigue. After the last training block, participants were invited to complete the questionnaires again and rest.

Once participants felt rested, they performed a six-shot Washout trial with the LS to mitigate aftereffects from training with the nonlinear springs. They then proceed to the Short-term Retention phase, which followed the same structure as the Baseline: two trials of six shots each with the LS, followed by a break and the completion of the questionnaires, and two trials of six shots with the transfer spring. The same structure was employed in the Long-term Retention phase performed on the second experimental day.

F. OUTCOME METRICS

1) TASK PERFORMANCE

Participants' performance was assessed by looking at both their accuracy in matching the target force and the consistency with which it was reproduced. Force accuracy was calculated as the absolute value of the **force error** (in Newtons), defined as the difference between the force at cube release and the target force. The **force consistency** (Force SD) was calculated as the standard deviation of the signed force error across the shots within each trial.

The relationship between the spring elongation and the force at release is non-linear in the GS and AGS springs. Therefore, we also evaluated the absolute **error** between the **spring elongation** at release and the target spring elongation.

2) EXPLORATION BEHAVIOR

To characterize participants exploratory behavior during training, we extracted a set of measures from the robot end-effector kinematic data that reflected how individuals interacted with the spring prior to release. Although exploration may take different forms from a behavioral point of view, within this experiment, we expected more exploration to be characterized by longer distance traveled by participants' hands/end-effector, in millimeters, from the onset of cube grasping to its release (**pre-release path length**). We also expected less smooth movements, calculated as the **number of directional changes** in the x-axis while holding the cube.

3) PERSONALITY QUESTIONNAIRES

Participants completed an online questionnaire administered via Qualtrics (Qualtrix XM, Provo, UT, USA) before the first experimental session. The questionnaire included

six personality-related sub-questionnaires. In particular, we included questions related to the **Transform of Challenge**, **Transform of Boredom** and **Curiosity** from the Autotelic Personality Questionnaire [35]; the **Achiever** and **Free Spirit** elements from the Hexad Gaming Style Questionnaire [36]; and the **Locus of Control** (LOC) questionnaire [37].

All questionnaires, except the LOC, used a seven-point Likert scale. Responses were normalized to values between 0 and 1 based on the theoretical minimum and maximum of each scale, with higher scores indicating stronger expression of the respective trait or gaming style. The LOC questionnaire consisted of 23 multiple-choice items plus six control questions. Raw scores (0 to 23) were linearly transformed to a continuous scale ranging from -1 (*Internal* LOC) to 1 (*External* LOC) to enhance interpretability and facilitate analysis. Internal LOC reflects the belief that outcomes are contingent on ones own actions, whereas external LOC attributes outcomes to external forces or chance.

G. STATISTICAL ANALYSIS

The hypotheses (H1–4) outlined in Section I were examined using Linear Mixed-Effects Models (LMMs), implemented with the `lmer` function from the `lmerTest` package in `R`. Statistical significance was defined as $p < 0.05$, and p-values were corrected for multiple comparisons using Holm.

1) LMM TO ANALYZE PERFORMANCE DURING TRAINING (H1)

We first evaluated the impact of the different spring types and individual personality factors on task performance—namely, absolute force error & SD and absolute spring elongation error—during training (Hypothesis H1). Since the dataset included many variables and potential interactions, we sequentially compared models using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to reduce the risk of overfitting and select stable models. When competing models showed similar fit, model selection was further guided by effect size comparisons. A complete model comparison is available in Appendix B. The selected model has the form:

$$Var_{per} = SpringType \times TrialNumber \times FS_c + (1|ID).$$

The *SpringType*—i.e., Linear, Gaussian, or AS-Gaussian—and *TrialNumber*—an ordinal from 0 (first training trial) to 27 (last training trial)—were included as independent variables. Note that the *SpringType* variable is not equivalent to the assigned training condition, as during catch trials, the Linear spring was rendered to all participants.

Only one personality trait remained after model reduction: the normalized and centered Free Spirit score (FS_c). Participant *ID* was included as a random intercept to account for inter-individual variability. The dependent variables were log-transformed to correct for their skewed distribution due to the absolute values.

2) LMM TO ANALYZE PARTICIPANTS' EXPLORATION BEHAVIOR DURING TRAINING (H2)

To analyze H2, we started with a complete model, as in the previous subsection, with the pre-release path length and number of directional changes as dependent variables. The selected model has the form:

$$Var_{beh} = (FS_c + CH_c) \times (SpringType \times TrialNumber) + (1|ID).$$

The fixed effects included *SpringType* and *TrialNumber*, together with the normalized and centered scores from the Transform of Challenge questionnaire (CH_c) and the Free Spirit questionnaire (FS_c). Participant *ID* was included as a random intercept to account for inter-individual variability.

3) LMM TO ANALYZE MOTOR LEARNING (H3)

To evaluate the impact of the different spring types and individual personality factors on performance improvements across experimental phases, we employed the following model:

$$Var_{learn} = (FS_c + CU_c) \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Here, *Condition* indicates the group to which participants were allocated (Linear, Gaussian, or AS-Gaussian), and *Stage* distinguishes between Baseline, STR, and LTR. Each *Stage* was divided into two trials, which was reflected in the variable *TrialNumber* (0 to 1). The normalized and centered scores of Free Spirit (FSc) and Curiosity (CUc) were incorporated as fixed effects after model reduction. Participant *ID* was included as a random intercept.

Only the log-transformed absolute force error and the force SD were included as dependent variables since the force–elongation relationship was always linear, and therefore, redundant. Data from the transfer task were not included.

4) LMM TO ANALYZE SKILL TRANSFER (H4)

To evaluate whether participants relied on force-based or positional-based information during the transfer task (H4), we fitted a separate LMM with spring elongation as the dependent variable. We did not use the spring elongation error, as it could lead to a misleading interpretation due to differences in target elongations between the main and transfer springs. Because trait- and condition-dependent effects were not of interest for this hypothesis, the resulting model is defined as follows:

$$Var_{Transfer} = TransTask \times Stage \times TrialNumber \times ShotNumber + (1|ID).$$

The *TransTask* indicates whether participants interacted with the main spring (0: target elongation 90 mm), or the transfer spring (1: target elongation 70 mm). The used dataset

included data from the Baseline, STR, and LTR phases. Consequently, *TrialNumber* ranged from 0 to 1. We also included *ShotNumber* (0 to 5), i.e., the order of shots within a trial, to capture changes across successive shots.

III. RESULTS

Complete LMM models and outputs, including the LMM full tables, are provided in Appendices B and C. To aid interpretation, Figs. 5 to 8 illustrate predicted changes in the dependent variables and associated 95% confidence intervals derived from the model estimates. Some of the predicted changes include participants with 10% above or below the average group personality trait, labeled as ''high'' or ''low'' levels, respectively. This margin was chosen to facilitate interpretation as it reflects a realistic and meaningful deviation from the average.

A. TASK PERFORMANCE DURING TRAINING (H1)

1) EFFECT OF SPRING TYPE IN TASK PERFORMANCE (H1.1)

Regarding **force accuracy**, participants who trained with the Linear or AS-Gaussian springs did not improve across training trials. However, participants who received the AS-Gaussian spring consistently exhibited lower force error than the linear spring group throughout training while receiving this non-linear spring (Fig. 5a, approximately 38% reduction; main effect of spring, $p < 0.001$). Participants who trained with the Gaussian spring, on the other hand, showed improvement across the training trials (Fig. 5a, itGaussianSpring $\times$ TrialNumber, $p = 0.011$) and outperformed the linear group by the end of training, with approximately 46% lower force error in the final trial (pairwise comparison of estimated marginal means at last training trial, $p < 0.001$).

Regarding **force variability**, a significant reduction over training was observed only for participants trained with the Gaussian spring (*GaussianSpring x TrialNumber*, $p = 0.040$). **Spring elongation error**, on the other hand, did not show significant effects of spring type or spring–trial interactions, but only a main effect of trial, suggesting a general improvement independent of the training dynamics (Fig. 5b, $p = 0.031$).

2) INFLUENCE OF PERSONALITY TRAITS IN TASK PERFORMANCE (H1.2)

Personality traits modulated task performance during training. Specifically, participants with higher **Free Spirit** scores showed worse initial performance when training with the Gaussian spring. A participant scoring 10% higher Free Spirit, for example, was predicted to show 51% more force error and 29% more spring elongation error at the beginning of training compared with an average participant training with the same spring (Fig. 5, $p = 0.003$ and $p = 0.019$, respectively). This performance difference was reduced as the training advanced, with only a (non-significant) 21% more force error and 10% more elongation error w.r.t. average participants in the Gaussian group at the end of the training.

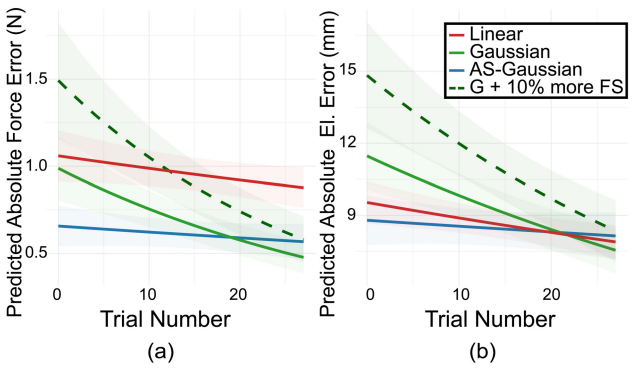


FIGURE 5. Prediction from the LMM to visualize performance during training. Shaded regions indicate 95% confidence intervals. (a) Evolution of the absolute force error along the 28 training trials. (b) Evolution of the absolute spring elongation error along the 28 training trials. El.: Spring Elongation, G: Gaussian, FS: Free Spiri.

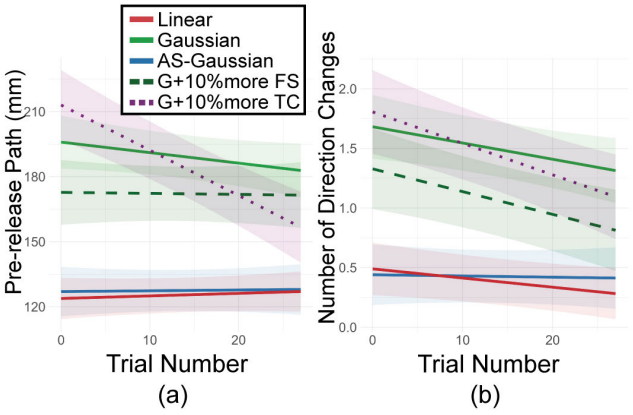


FIGURE 6. Prediction from the LMM to analyze participants' exploration behaviour during training. Shaded regions indicate 95% confidence intervals. (a) Evolution of the pre-release path length along the 28 training trials. (b) Evolution of the number of direction changes along the 28 training trials. G: Gaussian, FS: Free Spirit, TC: Transform of Challenge.

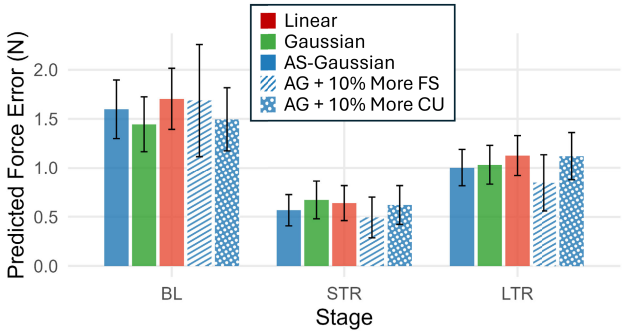


FIGURE 7. Evolution of the absolute force error along the baseline and the two retention phases. Predicted from the LMM designed to analyze motor learning with 95% confidence intervals. G: Gaussian; AG: Antisymetric Gaussian; FS: Free Spirit; CU: Curiosity.

B. EXPLORATORY BEHAVIOR DURING TRAINING (H.2)

1) OVERALL EXPLORATORY BEHAVIOR DURING TRAINING (H2.1) AND THE EFFECT OF SPRING TYPE (H2.2)

Overall, participants' exploratory behavior did not change significantly over training (Fig. 6, pre-release path length: $p = 1$, number of directional changes: $p = 0.524$).



FIGURE 8. Average spring elongation at release for each shot in BL, STR, and LTR. Colors differentiate between the main and transfer tasks. Black horizontal lines indicate the target position for the main task (90 mm), and dashed horizontal lines indicate the target position for the transfer task (70 mm).

We found distinct exploratory behaviors across spring types (H2.2). In particular, participants who trained with the Gaussian spring exhibited significantly higher **pre-release path length** and a greater **number of directional changes** at the beginning of the training compared to those who trained with the Linear spring (Fig. 6, $p < 0.001$ for both). No significant interaction between spring type and trial number was observed for these metrics, indicating that the differences did not significantly change across trials.

2) INFLUENCE OF PERSONALITY TRAITS IN EXPLORATION BEHAVIOR (H2.3)

Participants who trained with the Gaussian spring and with higher **Free Spirit** scores showed significantly lower pre-release path length compared to average participants receiving the same spring at the beginning of the training (Fig. 6, $p = 0.016$), while the lower number of directional changes did not reach significance after correction ($p = 0.524$). In contrast, participants scoring high in **Transform of Challenge** and training with the Gaussian spring displayed the opposite tendency, showing increased pre-release path length and number of directional changes at the beginning of the training when compared to average participants allocated to the same group (Fig. 6, $p = 0.003$ and $p = 0.054$). Moreover, a significant interaction between the Transform of Challenge and trial number when receiving the Gaussian spring indicated that these participants reduced both exploration metrics more rapidly over time than others (Fig. 6, pre-release path length: $p < 0.001$, number of directional changes: $p = 0.006$).

C. MOTOR LEARNING (H3)

1) OVERALL LEARNING (H3.1) AND EFFECT OF SPRING TYPE ON PERFORMANCE IMPROVEMENTS (H3.2)

Overall, participants significantly reduced the **force error** and **force SD** from Baseline (BL) to Short-term Retention (STR) (Fig. 7, $p < 0.001$ for both) and from BL to Long-term Retention (LTR) ($p = 0.004$ and $p < 0.001$ respectively). A reduction in both metrics was also observed from the first to the second trial during BL ($p < 0.001$ for both). However, contrary to our expectations, we did not find a significant effect of spring type on motor learning (H3.2).

2) INFLUENCE OF PERSONALITY TRAITS IN MOTOR LEARNING (H3.3)

We found interaction effects between the spring condition and personality traits on learning. In particular, individuals allocated in the AS-Gaussian group with high **Free Spirit** scores achieved a 12% greater reduction from BL to STR in force error when compared to average participants under the same condition. Conversely, participants allocated in the AS-Gaussian group with higher **Curiosity** scores demonstrated a 9% smaller reduction from BL to STR in force error compared to average individuals. However, none of those interactions remained significant after correction (*AS-Gaussian* × *PhaseSTR* × *Free Spirit*: $p = 0.076$, *AS-Gaussian* × *PhaseSTR* × *Curiosity*: $p = 0.280$). We also observed a slightly higher reduction in force SD among high **Free Spirit** participants allocated to the AS-Gaussian group from BL to STR compared to the average participants in the same group, though this difference was not significant after correction ($p = 0.157$).

D. TRANSFER TASK (H4)

Fig. 8 shows the average spring elongation at release across participants for each shot along the baseline and retention phases, including both the main and transfer tasks. The results from the LMM showed that participants adjusted the **spring elongation** at release from an average of 89.96 mm in the last shot of the main task at baseline (*TrialNumber* × *ShotNumber*: $p < 0.001$) to 74.83 mm in the first baseline shot of the transfer task (*TransTask*: $p < 0.001$). Both the *ShotNumber* and *TrialNumber*, as well as the interaction between them, showed significant effects during the transfer task at baseline, indicating that participants adapted to the new spring dynamics from the first to the subsequent shots and trials (all $p < 0.001$).

In Fig. 8 we can also observe that the first shot of the transfer task during both STR and LTR were, on average,

closer to the 90 mm target and the subsequent shots closer to the 70 mm target, compared to baseline. However, the *TransTask* variable showed significant interactions with the *Stage* phase, and its combination with *ShotNumber*, and *TrialNumber* (all $p < 0.001$) only at LTR. Yet, note that the performance degraded at the beginning of the LTR (see first shots in the main task in LTR in Fig. 8), and therefore, the main effect of *Stage* : *LTR* was large and significant. As a consequence, the interactions with *TransTask* might reflect how participants corrected the initially larger spring elongation error during the subsequent shots in the LTR phase.

IV. DISCUSSION

Given the number of hypotheses and statistical interactions examined, Table 10 in Appendix D provides a concise overview of the hypotheses and their level of support, facilitating the interpretation of the findings discussed in this section.

A. THE NON-LINEAR SPRING DYNAMICS MODULATED PARTICIPANTS' PERFORMANCE AND EXPLORATION BEHAVIOR DURING TRAINING

Overall, participants improved their performance during training. Yet, this improvement was significant only in reducing elongation error during training, independently of the spring received, while exclusively participants who trained with the Gaussian spring showed significant differences in force error or force SD by the end of training. Although this may appear contradictory, in the context of non-linear springs, identical spring elongation errors can lead to different force deviations depending on the springs force-elongation profile. The force-elongation curve of the AS-Gaussian and the Linear springs intersect at three points: one corresponding to the target force and two additional points (denoted as **a** and **b** in Fig. 3). Within the **a**–**b** interval, the AS-Gaussian spring produces forces closer to the target than the Linear spring for equivalent spring elongations. Outside this range, the opposite occurs.

This could be behind the differences in performance across springs, particularly the significantly better force accuracy observed in the AS-Gaussian throughout the training compared to the Linear. However, no significant differences were found between the Gaussian and Linear springs, despite the Gaussian also reducing force error within the **a**-**b** interval. The difference between the two non-linear springs may instead reflect how the forces are rendered. The AS-Gaussian spring creates a subtle "wall" just beyond the target force, due to its steep gradient, resembling performance-enhancing haptic strategies [27]. In contrast, the Gaussian spring reduces the rendered force after the target, which may feel unstable or "pushing away," thereby resembling performance-degrading haptic strategies [27]. Especially early in training, participants might not anticipate this "pushing" behavior, making them less likely to remain within the **a**–**b** interval and, consequently, less likely to exhibit reasonable force accuracy. As shown in Fig. 9, during the first training trial, participants training with the Gaussian spring exhibited larger spring elongations at cube release, compared to the other two springs. Yet, as training advanced, the Gaussian group improved their performance, outperforming the Linear one by the end of the training.

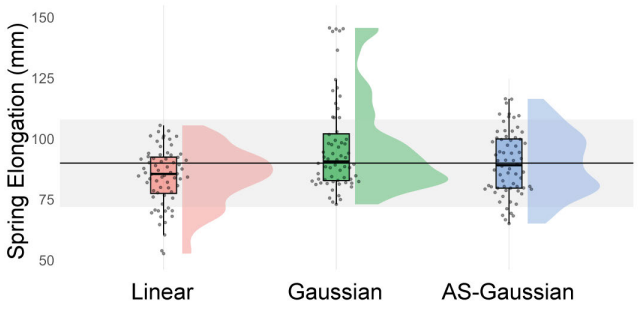


FIGURE 9. Spring elongations at cube release during the first training trial for each spring condition. Results are presented as raincloud plots, showing the data distribution and jittered individual observations, and are supplemented by boxplots. The black horizontal line marks the target elongation (90 mm), and the gray band denotes the region bounded by the two intersection points of the Antisymmetric Gaussian and Linear springs, i.e., the a–b interval.

Indeed, we hypothesized that the Gaussian spring would challenge participants and thereby improve their performance during training. We also expected that the sudden, noticeable change in spring dynamics, especially the decrease in force after the target force, would prompt them to actively explore the new force–elongation relationship. Our results partially support this: participants who trained with the Gaussian spring showed greater exploratory tendencies, as evidenced by greater pre-release path length and number of directional changes, especially during the first training trials, compared to those who trained with the Linear spring. Active exploration has been shown to support motor adaptation when variations directly inform the underlying task structure [40], and therefore, we expected this increased exploration behavior to ultimately enhance performance. While we found significant improvements in force accuracy, these were not accompanied by significant reductions in elongation error. It is therefore unclear whether better force accuracy was due to participants releasing the cube in the **a**-**b** spring elongation range, as explained before.

B. THE EFFECT OF THE SPRING DYNAMICS ON PERFORMANCE AND EXPLORATORY BEHAVIOR DEPENDS ON PERSONALITY TRAITS

We found some indications that personality traits played a role in how participants interacted with the system. Yet, given the number of personality traits measured, interaction terms with the spring dynamics, and the relatively modest sample size, these findings should be treated as exploratory.

Participants responses to the spring dynamics modulation likely depended not only on their perception of the haptic rendering but also on what they considered important to

achieve within the task. In the current task, when the physical interaction with the cube differed from what was expected (i.e., the Gaussian spring), participants who relied on a goal (''high'' Achievers) would not perform better than ''average/low'' Achievers, as they did not know what to do in order to ''achieve higher.'' Personality traits like the Transform of Challenge or the Achiever gaming style may require a clearly defined link between actions and goals to activate their motivational drive. Because the force–elongation relationship of the Gaussian spring was probably not intuitive, these participants may have lacked a concrete sense of progress or accomplishment, preventing their motivational traits from translating into better performance. This interpretation is supported by the results found regarding the exploratory metrics: participants high in Transform of Challenge scores showed increased exploratory behaviors when allocated to the Gaussian spring, suggesting that they tried hard to master the task, but their efforts did not yield measurable performance gains—likely due to insufficient task clarity or limitations to understand the feedback provided.

Free spirits, on the other hand, are intrinsically motivated by exploration, and therefore, we hypothesized that they would increase their exploratory metrics when the interaction invites discovery rather than direct goal achievement. Looking at the results, one would be surprised by the lower pre-release path length and the absence of significance on the number of directional changes in participants who scored high in Free Spirit when compared to average participants. Yet, it is possible that their exploration was performed *across* consecutive shots rather than *within* a shot. That is, rather than systematically exploring the force–elongation relationship within a shot, they might have adopted a ''trial-and-reset'' approach, testing the resulting score of shooting at different elongations. Because these participants are typically less goal-driven and more intrinsically motivated to ''try things out'' [36], they may have tolerated repeated ''failed'' attempts as part of their exploration process. This might be behind the worsened performance observed in this particular group at the beginning of the training. We depict this in Fig. 10: The upper row shows how a participant with one of the highest Free Spirit scores in our datasets performed across shots during training (left) compared with one of the participants with the lowest scores (right), both in the Gaussian spring group. The lower row shows the evolution of the pre-release path length for each of the exemplary participants.

Together, in conditions where the haptic rendering/guidance is intuitive, users might align their motivations with task objectives, as found in our previous work [34]. However, when the haptic rendering becomes ambiguous—as in the Gaussian spring—differences in exploratory drive and goal orientation begin to dominate performance outcomes and movement behaviors. Future designs of adaptive haptic systems should therefore consider not only the mechanical properties of feedback but also users' motivational profiles, potentially tailoring haptic strategies to individual tendencies toward exploration or goal pursuit. Furthermore, future

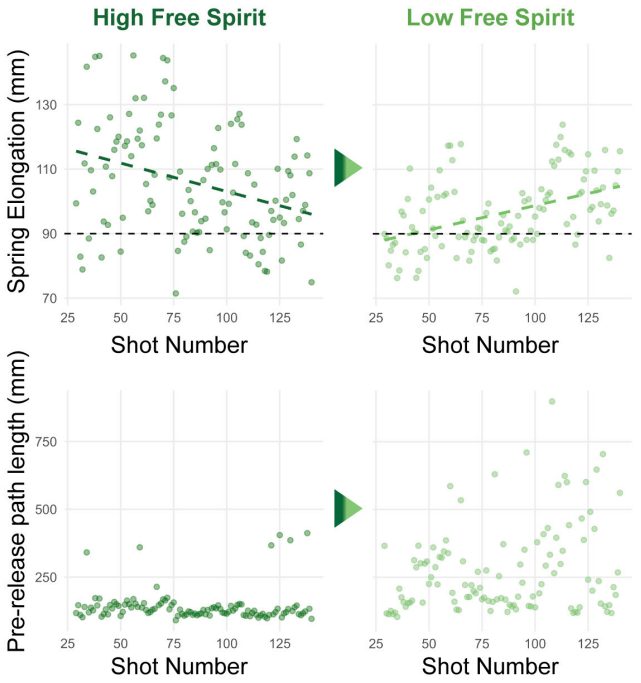


FIGURE 10. Spring elongation at release per shot (top panels) and pre-release path length per shot (bottom panels) for two representative participants training with the Gaussian spring. The left panels correspond to the participant with the highest Free Spirit score (dark green), and the right panels to the participant with the lowest score (light green). Black dashed horizontal lines indicate the target position, and green dashed lines represent linear regressions illustrating performance changes across training. For High Free Spirit vs. spring elongation: $R^2 = 0.11$, $p < 0.001$. For Low Free Spirit vs. spring elongation; $R^2 = 0.19$, $p < 0.001$.

directions include exploring how providing information about the system ''surreal'' dynamics would affect performance or task understanding in these particular participant profiles, compared to exploiting implicit learning without task dynamics information [41].

C. THE NON-SIGNIFICANT EFFECT OF SPRING DYNAMICS AND PERSONALITY ON MOTOR LEARNING

The few significant differences observed in performance and exploration behavior across springs during training did not result in differences in motor learning between groups. The same can be said of the interaction between spring dynamics and personality traits. In general, participants improved in both force and spring elongation accuracy after training, regardless of the spring type used during training.

As discussed in Section IV-A, under the nonlinear springs, the force associated with a given elongation error depended on the shape of the force–elongation curve. Consequently, the lower force errors observed with the AS-Gaussian spring, and later in the training with the Gaussian spring, may partly reflect the immediate benefits of the rendered dynamics or adaptation to those specific springs, rather than a more accurate and transferable force-control strategy. In line with the Guidance Hypothesis [42], it is possible that participants failed to create a long-lasting internal model of the target force because they relied on the ''guidance'' from the

nonlinear springs. Catch trials were strategically included every 4–5 trials to reduce this potential reliance, yet they may not have been sufficient; a longer training period and more catch trials may be necessary to form the internal model.

Another plausible explanation is that participants learned the target elongation, rather than the target force, and that the spring dynamics did not play a relevant role after all. As discussed in more detail in the next section, all training conditions shared the same successful target elongation. Participants could therefore have improved by learning a repeated pulling displacement, regardless of the force–elongation profile being rendered. The reported shoulder strain and muscle fatigue from the repetitive nature of the task might have exacerbated this. Muscle fatigue alters muscle spindle sensitivity [43] and degrades proprioceptive acuity, thereby altering joint-position reproduction [44] and reducing force-production capacity [45]. Fatigue may have altered the perceived force, especially towards the last training trials, crucial for the creation of the task internal model [46].

Similarly, the interactions between spring dynamics and personality traits observed during training did not result in significant differences in retention. No better performance was found for high Free Spirit participants allocated to the Gaussian spring when comparing baseline with STR; still, this is consistent with the training results: during training, although Free Spirit participants allocated to the Gaussian curve improved significantly, many of them probably did not fully grasp the relationship between their actions and task success by the end of the training. From the results in Fig. 5, it seems like they were still improving their performance at the end of the training, and therefore, it is an open question whether providing more training time would have resulted in better learning, when compared to average participants receiving the Gaussian spring.

The small differences observed between the baseline and retention phases for participants trained with the AS-Gaussian spring and who had high levels of Free Spirit or Curiosity were unexpected and should be interpreted with caution. Given the limited magnitude of those differences, the size of the confidence intervals, and the lack of significance after Holm correction, these effects may reflect statistical noise or incidental variability rather than robust learning differences. If these trends are not purely incidental, a possible explanation is that the AS-Gaussian profile supported different exploratory strategies depending on individual traits during training. Free Spirit participants may have been more sensitive to the localized increase in stiffness—the ''subtle wall''—and explored behavior around this region, whereas highly curiosity-driven participants may have engaged in broader exploration, including spring elongations around the plateau region. Nevertheless, this extra analysis was considered out of scope for this work; the observed effects were small, with wide confidence intervals, highlighting the potential limitations for drawing firm conclusions. Further work with more targeted measures of exploratory behavior and a larger sample size would be required to evaluate this explanation.

D. LEARNING THE TARGET FORCE VS. THE TARGET ELONGATION

The transfer task was included to test whether participants could reproduce and adapt a target force independently of positional or proprioceptive cues, i.e., whether they learned the target force or the spring elongation at release. During interaction with elastic objects, force and position are mechanically coupled, and users may combine force-related feedback with proprioceptive information about object deformation to perform the task [47].

We found that during the baseline transfer task, participants' first shot shifted toward the new target position, suggesting that force-related information contributed to their initial adjustment to the new stiffness. Yet, several more shots were needed to further approach the target elongation of the transfer spring. This baseline behavior is compatible with the findings of Mugge et al., who explored a similar task and estimated approximately equal contributions of force- and position-related information at a stiffness of about 108 N/m and a target force of 10 N [47], similar parameters as those used in our main linear spring, which had a stiffness of 111.1 N/m and the same target force.

In contrast, the first transfer shots at both short- and long-term retention remained closer to the previously trained elongation of 90 mm before rapidly approaching the new target elongation on subsequent shots. Thus, training did not appear to increase reliance on force-related information. This might be explained by the context-dependent relative contribution of force and position information, which allows the nervous system to downweight information that becomes less reliable as environmental conditions change [48]. The target elongation remained the same during training, while the nonlinear springs altered the force information experienced throughout the movement. Therefore, position information may have become a more reliable predictor of success during training compared to force. This is despite the continuing reposition of participants w.r.t. the robot. Changing participants' feet position relative to the robot may have disrupted reliance on a fixed global arm configuration, but relative displacement from the initial grasping position remained nevertheless available as a positional cue. Repeated practice may therefore have strengthened a displacement-based prior or a feedforward movement terminating near 90 mm, resulting in greater positional carryover when participants subsequently encountered the transfer spring. Because this characteristic was common to all training springs, it may also explain why we did not find differences between spring conditions at retention or transfer.

Nevertheless, the rapid correction after the first transfer shot in the retention phases indicates that force-related information remained available to support recalibration when the practiced displacement no longer produced the intended outcome. This behavior is consistent with evidence that motor

generalization depends on the history of prior actions and that errors arising when a learned solution becomes inappropriate can drive rapid adjustment to new task dynamics [49]. Future training protocols could vary the target elongation or force–position mapping across training trials to minimize the reliance on positional cues, for example, by presenting multiple randomized stiffnesses for the same target force. This would prevent a single displacement from consistently predicting success and help determine whether reducing the reliability of a fixed positional solution promotes the learning of target force generation.

E. IMPLICATIONS FOR FUTURE STROKE REHABILITATION RESEARCH

Although motivated by its potential application in post-stroke neurorehabilitation, this study should be interpreted as a proof of concept in healthy adults rather than as evidence of clinical effectiveness. Nevertheless, establishing whether the proposed approach produces measurable behavioral effects under controlled conditions is an important step before investigating them in a clinical population.

Several aspects should be considered before clinical translation. In the present study, the rendered dynamics influenced task accuracy and exploratory behavior during training, but these effects did not persist into the retention phases. Moreover, the clinical significance of these training effects remains unclear and warrants further investigation. People after stroke may present heterogeneous combinations of motor and somatosensory impairments that alter their perception of the rendered dynamics and use of force- and position-related information [2], [3]. The parameters in the non-linear spring equations, e.g., the curve width W, might need to be adapted for populations with compromised sensory capabilities. Formally determining the perceptual thresholds associated with different widths would require a dedicated psychophysical study.

The potential clinical relevance of our findings also needs further evaluation. For example, during training, the AS-Gaussian spring reduced force error by approximately 38% relative to the Linear spring, corresponding to an absolute difference of about 0.5 N, or 5% of the target force. This difference could be considered below the approximate force-discrimination thresholds reported for active arm movements at similar force levels in healthy participants [50]. However, because participants grasped and moved the device with a pinch-type grip, skin stretch and contact cues may also have contributed to force perception, limiting direct comparison with these thresholds. In addition, somatosensory sensitivity may be reduced or vary after stroke [2]. Future studies should evaluate movements and force ranges that allow the nonlinear features to be calibrated to each participants perceptual threshold, or employ setups with a larger range of motion and force to make these features more distinguishable before proceeding to clinical evaluation. Beyond these sensorimotor considerations, stroke can be accompanied by personality or behavioral changes that influence task engagement [51]. Therefore, the personality-related associations observed in healthy adults cannot be assumed to generalize directly to stroke survivors. Future studies should examine whether the selected personality measures remain valid and relevant after stroke and whether their associations with responses to haptic training are replicated in this population.

Future studies should first address the identified limitations, including positional reliance and fatigue, before assessing the method's feasibility and usability with stroke survivors and rehabilitation professionals across different sensorimotor profiles [26]. Nevertheless, the observed effects on force-generation performance and exploratory behavior provide a basis for refining the approach toward future clinical evaluation.

F. STUDY LIMITATIONS

Several additional limitations are important to highlight. Apart from the ones mentioned in previous sections, it is worth noting some procedural factors that may have influenced retention outcomes. The repetitive use of the same arm during training led to reported fatigue and shoulder strain, which could have affected both motivation and performance consistency during the first session. Because fatigue was not systematically measured, we cannot determine whether it increased performance variability, reduced learning, or masked differences among training conditions. Future studies should monitor perceived and objective fatigue and mitigate its effects through longer or performance-contingent rest periods, shorter training blocks, or improved arm support, e.g., as done in [10]. Alternatively, the training approach could be adapted to actions involving smaller muscle groups, such as pinching, for which force–position weighting differences have also been demonstrated [52].

Another limitation concerns the exploratory personality analysis. Although the sample was substantial for a motor-learning experiment, the inclusion of several personality variables and interaction terms limits the extent to which one can draw conclusions. Moreover, traits were examined separately, whereas individuals may express combinations of characteristics that jointly influence behavior. Future studies should replicate these findings in larger samples and examine multivariate personality profiles in relation to training dynamics.

Finally, because this study involved healthy participants, the findings cannot be assumed to generalize to stroke survivors or other rehabilitation populations. The present work should therefore be regarded as an initial step toward clinical translation rather than as validation of a rehabilitation intervention.

V. CONCLUSION

We investigated how altering the haptically perceived dynamics of virtual objects can enhance learning of precision force generation and whether personality traits modulate this effect. In a parallel design study, fifty participants trained

with a haptic device that rendered a virtual spring with either a linear, Gaussian, or Antisymmetric Gaussian force-elongation relationship, the latter two with zero derivative on the target force to be learned. We found that altering the object dynamics can increase task exploration and modulate performance during training. The effect seems to depend on participants' personality traits; when task dynamics are not fully understood, goal-oriented individuals may engage in a more systematic and extensive exploration before selecting the target force, whereas high Free Spirit individuals may show lower exploration, but higher shot-to-shot variability in the selected force. Interestingly, these differences did not necessarily translate into improved performance at the end of the training or into better motor learning. We also found that, during the retention phases, participants appeared to rely primarily on the learned target elongation rather than target force, requiring performance errors to shift back to force-based information when task dynamics changed. Future work should determine whether preventing reliance on a fixed pulling elongation and diminishing potential muscle fatigue effects would improve the effectiveness of our proposed method to train precision force generation. Clarifying how task dynamics, information about the tasks goal, and personality traits interact would further enable sensorimotor training to be strategically tailored to specific patient and therapeutic objectives.

APPENDIX A
PARTICIPANT DISTRIBUTION PER PERSONALITY TRAIT

Figure 11 illustrates the distribution of personality-trait levels across training conditions.

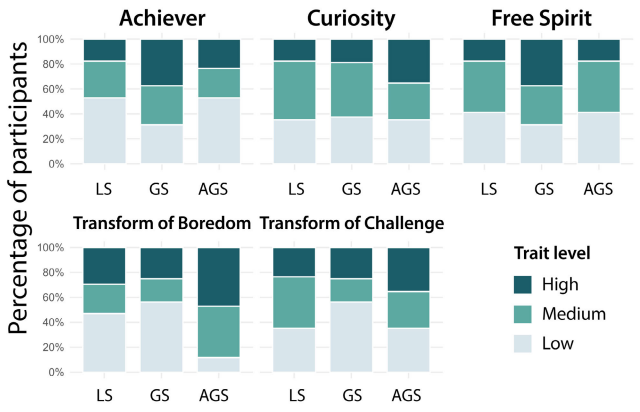


FIGURE 11. Distribution of participants across personality-trait levels and training conditions. Low, medium, and high levels were defined using the 33rd and 67th percentiles calculated across the full sample for each trait. The same trait-specific thresholds were then applied to all training conditions. LS: Linear Spring, GS: Gaussian Spring, AGS: Anti-symmetric Gaussian Spring.

APPENDIX B
MODEL SELECTION

Several candidate models were compared, varying in their inclusion of fixed effects, interaction terms, and combinations of personality traits. The naming convention for the following sub-sections in this Appendix matches that of the Statistical Analysis section of the main manuscript to facilitate correspondence between the hypothesis to be answered and its respective linear mixed models used to compare. Model selection was performed through stepwise comparison, guided by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). When competing models showed similar fit, model selection was further guided by effect size comparisons.

A. LMM TO ANALYZE PERFORMANCE DURING TRAINING (H1)

To compare these LMMs, we employed a dataset including information only from the training phase. The abbreviations used in the following models refer to the following variables: *SpringType*: Active spring during the corresponding dataframe, i.e., Linear, Gaussian, or AS-Gaussian; *TrialNumber*: an ordinal from 0 to 27 indicating the training trial; *ID*: Participant identifier number; FS_c: Centered and normalized score from the Free Spirit gaming style Questionnaire; AC_c: Centered and normalized score from the Achiever gaming style Questionnaire; CH_c: Centered and normalized score from the Transformation of Challenge sub-scale from the Autotelic Personality Questionnaire;.BO_c: Centered and normalized score from the Transformation of Boredom sub-scale from the Autotelic Personality Questionnaire; CU_c: Centered and normalized score from the Curiosity sub-scale from the Autotelic Personality Questionnaire; LOC_c: Centered and normalized score from the Locus of Control Questionnaire.

Model 1:

$$Var_{per} = SpringType \times TrialNumber \times (FS_c + AC_c + CH_c + BO_c + CU_c + LOC_c) + (1|ID).$$

Model 2:

$$Var_{per} = SpringType \times TrialNumber \times (FS_c + CH_c) + (1|ID).$$

Model 3:

$$Var_{per} = SpringType \times TrialNumber \times (AC_c + CU_c) + (1|ID).$$

Model 4 (Model chosen for manuscript):

$$Var_{per} = SpringType \times TrialNumber \times FS_c + (1|ID).$$

Model 5:

$$Var_{per} = SpringType \times TrialNumber \times AC_c + (1|ID).$$

Model 6:

$$Var_{per} = SpringType \times TrialNumber \times CH_c + (1|ID).$$

Model 7:

$$Var_{per} = SpringType \times TrialNumber \times BO_c + (1|ID).$$

Model 8:

$$Var_{per} = SpringType \times TrialNumber \times CU_c + (1|ID).$$

Model 9:

$$Var_{per} = SpringType \times TrialNumber \times LOC_c + (1|ID).$$

We compared models 1-9 using AIC and BIC. Results can be found in Table 1.

Model 4 and Model 7 exhibited the lowest AIC and BIC for both of the dependent variables. Because their fit was comparable, model selection was further guided by the magnitude and relevance of the effect sizes of interest. After comparing effect sizes across Models 4–9, Model 4 was retained, as it captured the most relevant effects for discussion. The traits included in Models 5, 6, and 8 showed no significant interactions, and the corresponding effects in Model 7 were considered small or non-relevant contributions.

TABLE 1. AIC and BIC values from models 1 to 9. These values were employed to select the best candidate to be the model to analyze performance during training.

	$\log(\lvert ForceError \rvert)$		$\log(\lvert SpringElongationError \rvert)$	
Model	AIC	BIC	AIC	BIC
Model 1	1050.36	1281.10	-69.66	161.08
Model 2	963.21	1068.09	-190.20	-85.31
Model 3	978.54	1083.43	-175.80	-70.91
Model 4	930.37	1003.79	-226.45	-153.03
Model 5	951.34	1024.76	-209.25	-135.83
Model 6	956.07	1029.49	-206.76	-133.34
Model 7	925.13	998.55	-230.48	-157.06
Model 8	952.17	1025.59	-208.40	-134.99
Model 9	962.69	1036.11	-157.43	-124.01

B. LMM TO ANALYZE PARTICIPANTS' EXPLORATION BEHAVIOR DURING TRAINING (H2)

The dataset and variables employed in the following models are the same as in the previous sub-section, with the only change being the dependent variables, as shown in the main manuscript.

Model 1:

$$Var_{beh} = SpringType \times TrialNumber \times (FS_c) + (1|ID).$$

Model 2:

$$Var_{beh} = SpringType \times TrialNumber \times (CH_c) + (1|ID).$$

Model 3:

$$Var_{beh} = SpringType \times TrialNumber \times (BO_c) + (1|ID).$$

Model 4 (Model chosen for manuscript):

$$Var_{beh} = SpringType \times TrialNumber \times (FS_c + CH_c) + (1|ID).$$

Model 5:

$$Var_{beh} = SpringType \times TrialNumber \times (FS_c + AC_c) + (1|ID).$$

Model 6:

$$Var_{beh} = SpringType \times TrialNumber \times (FS_c + BO_c) + (1|ID).$$

Model 7:

$$Var_{beh} = SpringType \times TrialNumber \times (FS_c + CU_c) + (1|ID).$$

Model 8:

$$Var_{beh} = SpringType \times TrialNumber \times (FS_c + LOC_c) + (1|ID).$$

We compared models 1-8 using AIC and BIC. Results can be found in Table 2. Given that the combination of Free Spirit and Challenge yielded the best fit for the dependent variable *DistanceTravelled* and showed comparable fit across models for *DirectionChanges*, we further examined effect sizes across models that included the same traits, i.e., Models 1, 2, and 7. As these models provided overlapping information and very similar AIC and BIC, Model 4 (including both traits) was retained for the main manuscript to ensure simplicity within the analysis while avoiding redundancy across model specifications.

TABLE 2. AIC and BIC values from models 1 to 8. These values were employed to select the best candidate to be the model to analyze exploration during training.

	DistanceTravelled		*DirectionChanges*	
Model	AIC	BIC	AIC	BIC
Model 1	14374.47	14447.89	3435.960	3509.379
Model 2	14318.50	14391.92	3445.93	3519.34
Model 3	14393.66	14467.08	3449.06	3522.48
Model 4	14274.57	14379.46	3443.860	3548.744
Model 5	14343.12	14448.00	3448.578	3553.462
Model 6	14344.05	14448.93	3442.646	3547.531
Model 7	14338.24	14443.12	3453.786	3558.670
Model 8	14358.44	14463.32	3460.331	3565.216

C. LMM TO ANALYZE MOTOR LEARNING (H3)

To compare the LMM to analyze Motor Learning, we employed a dataset excluding information from the training phase and transfer task. The only different variables

TABLE 3. AIC and BIC values from Models 1–10. These values were used to identify the best candidate model to analyze motor learning.

Model	AIC	BIC
Model 1	-73.98038	14.91040
Model 2	-70.74191	18.14887
Model 3	-74.73864	14.15214
Model 4	-71.34454	17.54624
Model 5	-75.73161	13.15917
Model 6	-43.28802	45.60276
Model 7	-69.29499	56.63361
Model 8	-65.31292	60.61568
Model 9	-55.21136	70.71724
Model 10	-65.24330	60.68531

included w.r.t. the previous sections are: *Condition*: with the group allocated; *Stage*, including the stage, i.e., Baseline, Short-term retention, or Long-term retention. The proposed models were the following.

Model 1:

$$Var_{learn} = FS_c \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 2:

$$Var_{learn} = CU_c \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 3:

$$Var_{learn} = CH_c \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 4:

$$Var_{learn} = BO_c \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 5:

$$Var_{learn} = AC_c \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 6:

$$Var_{learn} = LOC_c \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 7 (Model chosen for manuscript):

$$Var_{learn} = (FS_c + CU_c) \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 8:

$$Var_{learn} = (FS_c + CH_c) \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

TABLE 4. Results from the linear mixed-effects model to analyze spring elongation during training. *($p < 0.05$), **($p < 0.01$), ***($p < 0.001$). Std.: Standard; Corr.: Corrected; FS: Free Spirit. Lowercase 'c' denotes mean-centered questionnaire scores.

Variable	Estimate (β)	Std. Error	t value	p-value	Corr. p-value
(Intercept)	9.794e-01	2.053e-02	47.720	$< 2 \times 10^{-16}$	$< \mathbf{2 \times 10^{-16}}$***
SpringType Gaussian	8.023e-02	3.126e-02	2.567	0.01040	0.09361
SpringType AS-Gaussian	-3.516e-02	3.002e-02	-1.171	0.24185	1
TrialNumber	-3.044e-03	1.007e-03	-3.024	0.00255	**0.02546***
FS_c	2.048e-01	1.969e-01	1.041	0.29912	1
SpringType Gaussian : *TrialNumber*	-3.693e-03	1.739e-03	-2.124	0.03383	0.2706
SpringType AS-Gaussian : *TrialNumber*	1.806e-03	1.675e-03	1.078	0.28114	1
SpringType Gaussian : FS_c	9.095e-01	2.888e-01	3.149	0.00168	**0.01852***
SpringType AS-Gaussian : FS_c	-4.263e-01	3.283e-01	-1.298	0.19450	1
TrialNumber : FS_c	7.221e-03	9.565e-03	0.755	0.45042	1
SpringType Gaussian : *TrialNumber* : FS_c	-3.220e-02	1.608e-02	-2.002	0.04551	0.31859
SpringType AS-Gaussian : *TrialNumber* : FS_c	2.094e-02	1.812e-02	1.156	0.24804	1

TABLE 5. Results from the linear mixed-effects model to analyze force error during training. *($p < 0.05$), **($p < 0.01$), ***($p < 0.001$). Std.: Standard; Corr.: Corrected; FS: Free Spirit. Lowercase 'c' denotes mean-centered questionnaire scores.

Variable	Estimate (β)	Std. Error	t value	p-value	Corr. p-value
(Intercept)	2.514e-02	3.080e-02	0.816	0.415075	1
SpringType Gaussian	-3.036e-02	4.727e-02	-0.642	0.520911	1
SpringType AS-Gaussian	-2.075e-01	4.541e-02	-4.568	5.49e-06	$\mathbf{6.59e-05}$***
TrialNumber	-3.044e-03	1.529e-03	-1.991	0.046674	0.42007
FS_c	2.065e-01	2.952e-01	0.699	0.484915	1
SpringType Gaussian : *TrialNumber*	-8.662e-03	2.640e-03	-3.281	0.001061	**0.0106***
SpringType AS-Gaussian : *TrialNumber*	6.751e-04	2.544e-03	0.265	0.790767	1
SpringType Gaussian : FS_c	1.584e+00	4.369e-01	3.627	0.000301	**0.00331****
SpringType AS-Gaussian : FS_c	-7.242e-01	4.964e-01	-1.459	0.144899	0.86939
TrialNumber : FS_c	7.207e-03	1.452e-02	0.496	0.619809	1
SpringType Gaussian : *TrialNumber* : FS_c	-4.234e-02	2.442e-02	-1.734	0.083203	0.64882
SpringType AS-Gaussian : *TrialNumber* : FS_c	4.802e-02	2.751e-02	1.746	0.081103	0.64882

TABLE 6. Results from the linear mixed-effects model to analyze Distance traveled during training. *($p < 0.05$), **($p < 0.01$), ***($p < 0.001$). Std.: Standard; Corr.: Corrected; FS: Free Spirit; CH: Transform of Challenge. Lowercase 'c' denotes mean-centered questionnaire scores.

Variable	Estimate (β)	Std. Error	t value	p-value	Corr. p-value
(Intercept)	123.816	4.866	25.443	$< 2 \times 10^{-16}$	$\mathbf{< 2 \times 10^{-16}}$***
SpringType Gaussian	72.105	6.242	11.552	$< 2 \times 10^{-16}$	$\mathbf{< 2 \times 10^{-16}}$***
SpringType AS-Gaussian	3.182	5.865	0.542	0.587579	1
TrialNumber	0.118	0.189	0.626	0.531608	1
FS_c	-34.330	47.986	-0.715	0.475890	1
CH_c	3.629	40.752	0.089	0.929162	1
SpringType Gaussian : *TrialNumber*	-0.603	0.330	-1.827	0.067930	0.88308
SpringType AS-Gaussian : *TrialNumber*	-0.081	0.313	-0.261	0.794388	1
SpringType Gaussian : FS_c	-197.508	60.503	-3.264	0.001125	**0.01576***
SpringType AS-Gaussian : FS_c	39.333	67.584	0.582	0.560682	1
SpringType Gaussian : CH_c	167.537	45.395	3.691	0.000233	**0.00349****
SpringType AS-Gaussian : CH_c	-22.026	49.418	-0.446	0.655884	1
TrialNumber : FS_c	0.031	1.792	0.018	0.986001	1
TrialNumber : CH_c	-1.115	1.672	-0.667	0.504914	1
SpringType Gaussian : *TrialNumber* : FS_c	4.345	3.183	1.365	0.172487	1
SpringType AS-Gaussian : *TrialNumber* : FS_c	0.359	3.511	0.102	0.918654	1
SpringType Gaussian : *TrialNumber* : CH_c	-14.912	2.479	-6.015	2.31×10^{-9}	$\mathbf{3.7 \times 10^{-8}}$***
SpringType AS-Gaussian : *TrialNumber* : CH_c	1.422	2.659	0.535	0.592942	1

TABLE 7. Results from the linear mixed-effects model to analyze Directional Changes during training. *($p < 0.05$), **($p < 0.01$), ***($p < 0.001$). Std.: Standard; Corr.: Corrected; FS: Free Spirit; CH: Transform of Challenge. Lowercase 'c' denotes mean-centered questionnaire scores.

Variable	Estimate (β)	Std. Error	t value	p-value	Corr. p-value
(Intercept)	0.490	0.112	4.372	3.24×10^{-5}	$\mathbf{3.5 \times 10^{-4}}$***
SpringType G	1.192	0.125	9.539	$< 2 \times 10^{-16}$	$\mathbf{< 2 \times 10^{-16}}$***
SpringType AG	-0.049	0.117	-0.419	0.67544	1
TrialNumber	-0.008	0.004	-2.059	0.03973	0.5243
FS_c	-1.008	1.113	-0.905	0.36802	1
CH_c	-1.395	0.927	-1.504	0.13550	1
SpringType Gaussian : *TrialNumber*	-0.006	0.007	-0.914	0.36101	1
SpringType AS-Gaussian : *TrialNumber*	0.007	0.006	1.080	0.28040	1
SpringType Gaussian : FS_c	-2.523	1.212	-2.083	0.03745	0.5243
SpringType AS-Gaussian : FS_c	0.599	1.356	0.442	0.65879	1
SpringType Gaussian : CH_c	2.638	0.906	2.914	0.00363	**0.05441**·
SpringType AS-Gaussian : CH_c	0.924	0.988	0.935	0.34981	1
TrialNumber : FS_c	0.026	0.035	0.749	0.45424	1
TrialNumber : CH_c	0.046	0.033	1.406	0.15995	1
SpringType Gaussian : *TrialNumber* : FS_c	-0.081	0.063	-1.291	0.19687	1
SpringType AS-Gaussian : *TrialNumber* : FS_c	-0.015	0.069	-0.218	0.82732	1
SpringType Gaussian : *TrialNumber* : CH_c	-0.174	0.049	-3.556	0.00039	**0.00624****
SpringType AS-Gaussian : *TrialNumber* : CH_c	-0.050	0.052	-0.945	0.34474	1

Model 9:

$$Var_{learn} = (FS_c + BO_c) \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

Model 10:

$$Var_{learn} = (FS_c + AC_c) \times (Condition \times Stage + TrialNumber) + Stage \times TrialNumber + (1|ID).$$

TABLE 8. Results from the linear mixed-effects model to analyze motor learning. *(p < 0.05), **(p < 0.01), ***(p < 0.001). Std.: Standard; Corr.: Corrected; FS: Free Spirit; CU: Curiosity; STR: Short-term retention; LTR: Long-term retention. Lowercase 'c' denotes mean-centered questionnaire scores.

Variable	Estimate (β)	Std. Error	t value	p-value	Corr. p-value
(Intercept)	0.232	0.040	5.729	5.96×10^{-8}	**1.79e-06*** **
FS_c	-0.534	0.380	-1.404	0.16278	1
CU_c	0.623	0.297	2.096	0.03818	0.7255
Condition Gaussian	-0.072	0.054	-1.326	0.18773	1
Condition AS-Gaussian	-0.028	0.053	-0.530	0.59727	1
Stage STR	-0.426	0.066	-6.451	6.64×10^{-10}	**2.12e-08*** **
Stage LTR	-0.181	0.047	-3.865	0.000145	**0.00406** *
TrialNumber	-0.196	0.033	-5.938	1.07×10^{-8}	**3.32e-07*** **
Condition Gaussian : *Stage* STR	0.093	0.059	1.565	0.119028	1
Condition AS-Gaussian : *Stage* STR	-0.024	0.058	-0.416	0.677450	1
Condition Gaussian : *Stage* LTR	0.034	0.059	0.572	0.567806	1
Condition AS-Gaussian : *Stage* LTR	-0.022	0.058	-0.380	0.704502	1
$\mathbf{FS_c}$: *Condition* Gaussian	1.343	0.554	2.425	0.016995	0.3569
$\mathbf{FS_c}$: *Condition* AS-Gaussian	0.768	0.658	1.168	0.245425	1
$\mathbf{FS_c}$: *Stage* STR	1.328	0.454	2.924	0.003806	0.09134
$\mathbf{FS_c}$: *Stage* LTR	0.351	0.401	0.875	0.382435	1
$\mathbf{FS_c}$: *TrialNumber*	-0.222	0.214	-1.039	0.299804	1
$\mathbf{CU_c}$: *Condition* Gaussian	-1.479	0.471	-3.139	0.002198	0.05935
$\mathbf{CU_c}$: *Condition* AS-Gaussian	-0.910	0.450	-2.024	0.045476	0.81858
$\mathbf{CU_c}$: *Stage* STR	-0.573	0.354	-1.618	0.106956	1
$\mathbf{CU_c}$: *Stage* LTR	-0.753	0.314	-2.397	0.017362	0.3569
$\mathbf{CU_c}$: *TrialNumber*	0.152	0.164	0.923	0.356944	1
Stage STR : *TrialNumber*	0.259	0.047	5.545	8.13×10^{-8}	**2.36e-06*** **
Stage LTR : *TrialNumber*	0.063	0.047	1.340	0.181441	1
$\mathbf{FS_c}$: *Condition* Gaussian : *Stage* STR	-1.478	0.608	-2.430	0.015880	**0.34936***
$\mathbf{FS_c}$: *Condition* AS-Gaussian : *Stage* STR	-2.165	0.722	-2.997	0.003026	**0.07564** *
$\mathbf{FS_c}$: *Condition* Gaussian : *Stage* LTR	-0.243	0.608	-0.400	0.689477	1
$\mathbf{FS_c}$: *Condition* AS-Gaussian : *Stage* LTR	-1.313	0.722	-1.818	0.070405	1
$\mathbf{CU_c}$: *Condition* Gaussian : *Stage* STR	0.479	0.518	0.926	0.355358	1
$\mathbf{CU_c}$: *Condition* AS-Gaussian : *Stage* STR	1.248	0.494	2.527	0.012189	0.28034
$\mathbf{CU_c}$: *Condition* Gaussian : *Stage* LTR	0.874	0.518	1.690	0.092490	1
$\mathbf{CU_c}$: *Condition* AS-Gaussian : *Stage* LTR	1.519	0.494	3.076	0.002359	0.06134

We compared models 1-10 using AIC and BIC. Results can be found in Table 3.

In this case, all models showed a very similar fit. When Curiosity and Free Spirit traits were included in the model, only those models showed significant and meaningful effect sizes. When comparing the size effect in Models 1, 2, and 7 (the ones including those traits), they provided overlapping information; therefore, for the sake of simplicity and clearer interpretation, Model 7 was selected for the final analysis, as it provided the most relevant results for the conclusions.

APPENDIX C
LINEAR MIXED MODELS OUTPUT

See tables 3–9.

APPENDIX D
TABLE SUMMARIZING HYPOTHESES AND THEIR LEVEL OF SUPPORT

See table 10.

TABLE 9. Results from the linear mixed-effects model to analyze the transfer task during the retention phases. *(p < 0.05), **(p < 0.01), ***(p < 0.001). Std.: Standard; Corr.: Corrected; Tr: Transfer; STR: Short-term retention; LTR: Long-term retention. Lowercase 'c' denotes mean-centered questionnaire scores.

Variable	Estimate (β)	Std. Error	t value	p-value	Corr. p-value
(Intercept)	82.255	1.274	64.579	$< 2 \times 10^{-16}$	$< \mathbf{2 \times 10^{-16}}$***
Task Tr	-7.425	1.768	-4.199	2.74×10^{-5}	**2.47e-04***
Stage STR	6.824	1.768	3.859	0.000116	**9.26e-04***
Stage LTR	17.495	1.768	9.895	$< 2 \times 10^{-16}$	$< \mathbf{2 \times 10^{-16}}$***
TrialNumber	9.169	1.768	5.185	2.28×10^{-7}	**2.96e-06***
ShotNumber	2.277	0.413	5.515	3.75×10^{-8}	**5.62e-07***
Task Tr : *Stage* STR	-1.800	2.501	-0.720	0.471801	0.5155
Task Tr : *Stage* LTR	-13.949	2.501	-5.578	2.61×10^{-8}	**4.18e-07***
Task Tr : *TrialNumber*	-15.019	2.504	-5.998	2.20×10^{-9}	**3.96e-08***
Stage STR : *TrialNumber*	-8.752	2.501	-3.500	0.000471	**0.0033****
Stage LTR : *TrialNumber*	-19.577	2.501	-7.829	6.46×10^{-15}	**1.36e-13***
Task Tr : *ShotNumber*	-4.162	0.584	-7.126	1.24×10^{-12}	**2.49e-11***
Stage STR : *ShotNumber*	-1.661	0.584	-2.843	0.004490	**0.02245***
Stage LTR : *ShotNumber*	-5.013	0.584	-8.583	$< 2 \times 10^{-16}$	**3e-16***
TrialNumber : *ShotNumber*	-2.966	0.584	-5.078	4.01×10^{-7}	**4.81e-06***
Task Tr : *Stage* STR : *TrialNumber*	4.836	3.539	1.367	0.171834	0.5155
Task Tr : *Stage* LTR : *TrialNumber*	16.662	3.539	4.709	2.59×10^{-6}	**2.85e-05***
Task Tr : *Stage* STR : *ShotNumber*	0.936	0.826	1.133	0.257208	0.5155
Task Tr : *Stage* LTR : *ShotNumber*	4.497	0.826	5.445	5.52×10^{-8}	**7.73e-07***
Task Tr : *TrialNumber* : *ShotNumber*	4.787	0.827	5.791	7.60×10^{-9}	**1.29e-07***
Stage STR : *TrialNumber* : *ShotNumber*	2.620	0.826	3.172	0.001526	**9.16e-03****
Stage LTR : *TrialNumber* : *ShotNumber*	5.809	0.826	7.034	2.40×10^{-12}	**4.56e-11***
Task Tr : *Stage* STR : *TrialNumber* : *ShotNumber*	-1.809	1.169	-1.548	0.121770	0.48708
Task Tr : *Stage* LTR : *TrialNumber* : *ShotNumber*	-5.163	1.169	-4.418	1.02×10^{-5}	**0.0001***

TABLE 10. Summary of the hypotheses, their level of support, and the main findings.

Hypothesis	Main-text section	Support	Summary of main findings
H1.1	Results in Section III-A1 and Discussion in Section IV-A	Partially supported	• The p redicted ordering across spring types regarding performance during training was not observed, but the elongation error improved irrespective of spring type. • The **AS-Gaussian** Spring produced lower force error than the Linear condition throughout training. • The **Gaussian** Spring improved across trials and outperformed the Linear condition only at the end, in both force error and force variability.
H1.2	Results in Section III-A2 and Discussion in Section IV-B	Not supported	• The hypothesized benefits of goal orientation and perceived control were not observed. • Higher Free Spirit scores were associated with poorer initial performance in the **Gaussian** Spring.
H2.1	Results in Section III-B1 and Discussion in Section IV-B	Not supported	• Neither pre-release path length nor the number of directional changes decreased significantly over training.
H2.2	Results in Section III-B1 and Discussion in Section IV-B	Partially supported	• The **Gaussian** Spring was associated with greater pre-release path length and more directional changes than the Linear condition at the beginning of training. • Comparable evidence was not found for the **AS-Gaussian** Spring.
H2.3	Results in Section III-B2 and Discussion in Section IV-B	Not supported	• In the Gaussian condition, higher Free Spirit scores were associated with lower pre-release path length. • Higher Transform of Challenge scores were associated with greater exploration metrics. • It is not clear whether our exploration metrics reflect direct exploration or different exploration styles
H3.1	Results in Section III-C1 and Discussion in Section IV-C	Supported	• Force error and force variability decreased from baseline to both short- and long-term retention, irrespective of training condition.
H3.2	Results in Section III-C1 and Discussion in Section IV-C	Not supported	• Motor learning did not differ significantly across spring conditions.
H3.3	Results in Section III-C2 and Discussion in Section IV-C	Not supported	• Free Spirit and Curiosity showed small condition-dependent trends in the **AS-Gaussian** group, but none remained significant after correction.
H4	Results in Section III-D and Discussion in Section IV-D	Not supported	• Initial transfer shots at short- and long-term retention remained closer to the trained elongation than to the new target elongation. • Participants recalibrated rapidly toward the new target elongation in the second transfer shot during STR and LTR.

DATA AVAILABILITY

The dataset used in this study is publicly accessible at: https://doi.org/10.5281/zenodo.23237175

ACKNOWLEDGMENT

The authors sincerely thank Dr. Amy Bellitto for her support during manuscript preparation and Toranj Ahmadniya for her hard work and assistance with the final phase of data collection.

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