Experimental Brain Research (2024) 242:1349–1359
https://doi.org/10.1007/s00221-024-06828-5

RESEARCH ARTICLE

Healthy adults favor stable left/right hand choices over performance at an unconstrained reach-to-grasp task

Taewon Kim[1,3,4] · Ruiwen Zhou[2] · Samah Gassass[1] · Téa Soberano[1] · Lei Liu[2] · Benjamin A. Philip[1]

Received: 10 October 2023 / Accepted: 25 March 2024 / Published online: 2 April 2024

Abstract
Reach-to-grasp actions are fundamental to the daily activities of human life, but few methods exist to assess individuals' reaching and grasping actions in unconstrained environments. The Block Building Task (BBT) provides an opportunity to directly observe and quantify these actions, including left/right hand choices. Here we sought to investigate the motor and non-motor causes of left/right hand choices, and optimize the design of the BBT, by manipulating motor and non-motor difficulty in the BBT's unconstrained reach-to-grasp task. We hypothesized that greater motor and non-motor (e.g. cognitive/perceptual) difficulty would drive increased usage of the dominant hand. To test this hypothesis, we modulated block size (large vs. small) to influence motor difficulty, and model complexity (10 vs. 5 blocks per model) to influence non-motor difficulty, in healthy adults ($n = 57$). Our data revealed that increased motor and non-motor difficulty led to lower task performance (slower task speed), but participants only increased use of their dominant hand only under the most difficult combination of conditions: in other words, participants allowed their performance to degrade before changing hand choices, even though participants were instructed only to optimize performance. These results demonstrate that hand choices during reach-to grasp actions are more stable than motor performance in healthy right-handed adults, but tasks with multifaceted difficulties can drive individuals to rely more on their dominant hand.

Keywords (4 to6): hand choice · Reaching and grasping · Task difficulty · Block-building task

Introduction

Our everyday actions often involve the use of one hand over the other, which requires an implicit or explicit decision about which hand to use (Oldfield 1971; Gabbard and Rabb 2000; Sainburg 2002; Scharoun et al. 2016). This decision takes on special relevance for patients with unilateral impairment of the upper limb, especially their dominant hand (DH) (Philip et al. 2020). Such unilateral impairment occurs frequently after neurological conditions such as stroke (Mani et al. 2013), but also impacts the life of patients with chronic peripheral injuries, e.g. upper extremity peripheral nerve injury (Wojtkiewicz et al. 2015). After peripheral nerve injury to the DH, patients continue using their affected hand whenever possible, despite their uninjured hand being more dexterous (Philip et al. 2022b). Therefore, encouraging compensation with the use of a healthy non-dominant hand (NDH) is crucial for these patients to regain their ability to function normally during daily activities. However, despite the importance of hand dominance and choice for everyday life and rehabilitation, few studies have investigated the factors that influence hand choice during reach-to-grasp actions in healthy adults.

Previous work has identified the role of individual factors in some hand choice tasks, but rarely how those factors integrate and interact in an unconstrained environment. Healthy adults use their NDH to reach to more of the workspace when visual feedback is unavailable (Przybyla et al.

Communicated by Winston D Byblow.

✉ Benjamin A. Philip
bphilip@wustl.edu

1 Program in Occupational Therapy, Washington University School of Medicine, St. Louis, MO, USA

2 Department of Biostatistics, Washington University School of Medicine, St. Louis, MO, USA

3 Department of Kinesiology, The Pennsylvania State University, University Park, PA, USA

4 Department of Physical Medicine and Rehabilitation, Penn State College of Medicine, Hershey, PA, USA

2013); and use their DH to reach to more of the workspace when the reached-to object will be used in a more complex task (e.g. tool use instead of simple pickup) regardless of grasp difficulty (Mamolo et al. 2004; Leconte and Fagard 2006; Bryden et al. 2011; Stone et al. 2013), or under greater cognitive load (Liang et al. 2018b). However, most of these studies involved constrained two-dimensional movements (e.g. Przybyla et al. 2013; Liang et al. 2018b) or choices limited to 3–5 target locations (e.g. Mamolo et al. 2004; Leconte and Fagard 2006; Bryden et al. 2011). Moreover, it remains unclear how well these results integrate, given their different task contexts. Most importantly, none of these studies modified task difficulty in both sensorimotor and cognitive-perceptual aspects, thus leaving unanswered questions about how motor and non-motor difficulties might interact.

The Block Building Task (BBT) provides a means to measure hand choices over time in unconstrained situations, with the potential to modify both motor and non-motor aspects of the task (Gonzalez and Goodale 2009; Stone et al. 2013). The BBT requires participants to pick up Lego blocks (The Lego Group, Billund, Denmark) and incorporate them into a simple model. The task naturally induces the participant to choose one hand for reaching and grasping each block, followed by bimanual interaction to construct the model. Importantly, this task allows direct quantification of left/right-hand choices for reach-to-grasp action in an unconstrained environment, in the context of complex object manipulations (building the model with the grasped blocks). Recently, this task has been used in peripheral nerve injury patients to illustrate the stability of hand choice after peripheral nerve injuries to the dominant hand, and it is sensitive to the interaction between peripheral nerve injury and hand dominance (Philip et al. 2022b).

The BBT has been used as a rapid and feasible measurement tool of hand choice during reaching and grasping actions in unconstrained environments (Gonzalez et al. 2006, 2007), but "hand choice" is a task-dependent construct that depends on multiple visuomotor demands and contextual factors (Bryden et al. 2011; Stone et al. 2013; Stone and Gonzalez 2014). Therefore, to understand the relevance of a hand choice assessment, we must understand which factors drive its specific results. In this study, we sought to identify the specific impact of two factors: the sensorimotor challenges of manipulating smaller objects ("motor difficulty" for brevity) and the cognitive/perceptual challenges of grouping the blocks into larger sets that require more complex constructions ("non-motor difficulty").

Both motor and non-motor difficulty are known to influence grasp behavior and selection. As an example of motor demands, healthy adults typically select stable grasps over natural grasps (Klein et al. 2021), but this is modulated by non-motor demands: when people have the option to choose grasps to visible or non-visible object endpoints, they prefer visual guidance over comfort (Voudouris et al. 2012) or smaller movements (Paulun et al. 2014). These influences should extend to reach-to-grasp context, because arm movement and selection are influenced by the final grasp's comfort (Janssen et al. 2009), function (Randerath et al. 2009), and affordances (Baumard et al. 2023). In the BBT, one study found that hand choice was influenced by obstacles and object sizes, but they provided a relatively weak difficulty modulation (their high-difficulty objects are equivalent to our low-difficulty objects), and the study confounded those two factors with stabilization demands (Stone et al. 2013).

In this study, we aimed to investigate how motor and non-motor factors can modulate left/right hand choices in the BBT's unconstrained reach-to-grasp context. We hypothesized that greater motor and non-motor (e.g. cognitive/perceptual) difficulty would drive increased usage of the DH during reaching and grasping. We modulated motor difficulty in the BBT by changing block sizes (Small vs. Large), and non-motor difficulty by changing model complexity (10 vs. 5 blocks per model). In addition, we sought to determine which BBT variant would be most functionally relevant by identifying which variant would best correlate with NDH precision drawing performance (Philip et al. 2023).

Methods

Study overview

This was cross-sectional single-arm study involving a single laboratory visit. The study was approved by the local Institutional Review Board ethics committee and all participants gave informed consent before participating in the study. Data were stored and managed via the Research Electronic Data Capture system (Harris et al. 2009).

Participants

Fifty-seven right-handed healthy adults (3 males), age range 22–51 years (28 ± 7; see Fig. 1 for age distribution), participated in this experiment. Participants were recruited without balancing genders because previous studies revealed no gender difference in the Block Building Task (BBT) (Gonzalez and Goodale 2009). The inclusion criteria were: right handed as determined by Edinburgh Handedness Inventory score 50+ (Oldfield 1971), normal or corrected-to-normal vision (self-report) and fluency in speaking, reading, and writing English. Exclusion criteria included individuals who have motor disabilities or impairments affecting the

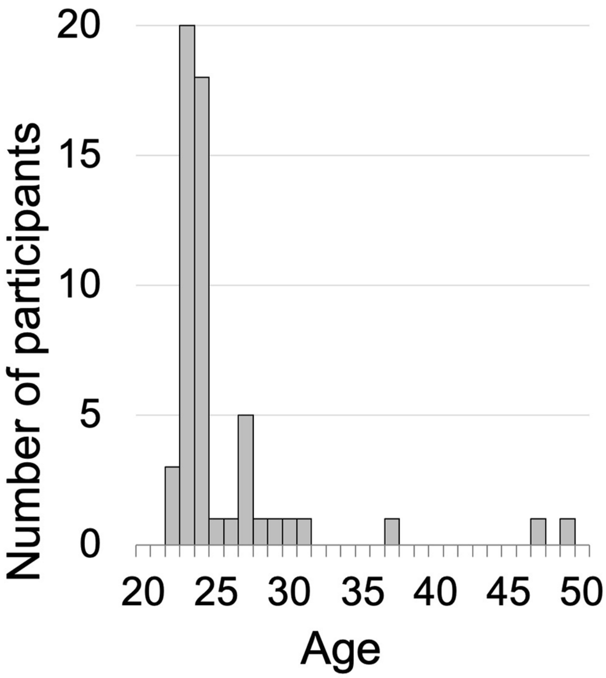

Fig. 1 Age distribution of participants

upper limb (self-report), and those who would be unable to come to campus to complete the tasks on site. All participants were recruited from the Washington University in St. Louis community to minimize risks during the COVID-19 pandemic (i.e. recruited from individuals who were already coming onto campus).

Sample size was determined from a power analysis based on preliminary data from a subset of the participants ($n = 19$). Based on the mean and variance-covariance matrices in the preliminary data, for each precision drawing variable (see below) to distinguish between the 4 BBT variants, we needed 33–40 participants to achieve power ≥ 0.8. Based on this power analysis, participants were recruited toward an $n = 40$ goal with an additional 10% margin in case of screening failures, leading to $n = 44$.

Thirteen additional participants had previously been recruited to perform an identical version of the BBT without the precision drawing task. These participants were included in our primary analyses (i.e. all analyses that do not mention the precision drawing task), for a total $n = 57$.

Materials and procedures

Block building task

The Block Building Task (Gonzalez et al. 2007; Stone et al. 2013; Philip et al. 2022a) directly measured hand use during precision reach-to-grasp movements in an unconstrained environment. Participants sat in front of a table with 40 Lego blocks: 4 or 8 copies each of 10 or 5 block types, in standardized locations. Participants were presented with a "model," an abstract construction containing 5 or 10 blocks (one of each type). Participants built the model on a small Lego base plate, as shown in Fig. 2. The experimenter's model remained in view until the participant finished their model, at which point both models (the experimenter's and the participant's) were removed from the table. This was repeated until participants picked up all 40 blocks (i.e. after 4 or 8 models); blocks were not replaced between models, so a full repetition of the task involved the participant picking up all 40 blocks.

Each participant repeated the task 4 times, one each for 4 different variants to modulate task difficulty, in a 2×2 design that varied motor difficulty via Block Size (Large, 2.2 ± 1.4 cm3; vs. Small, 0.8 ± 1.6 cm3), and non-motor difficulty via Quantity (10 vs. 5 blocks per model). Example models for each condition are shown in Fig. 3. The layout of blocks on the table was different for each variant, but those layouts were identical across participants. Within each layout, block position was randomized, except that each quadrant of the

Fig. 2 Block Building Task. Figure reproduced with permission from Philip et al. (2022a). Participants build 4 models (bottom center) from 40 Lego bricks. Participants are instructed to build quickly and accurately, but receive no instructions about hand use

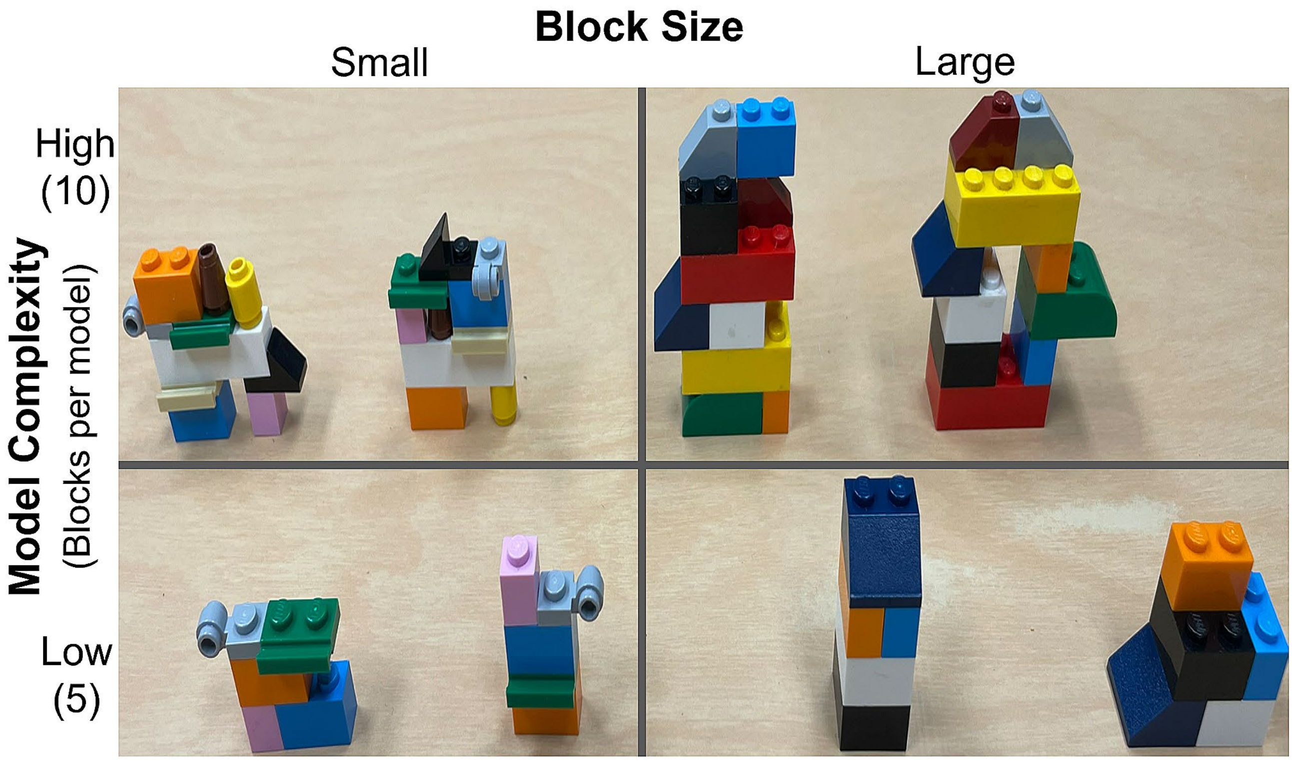

Fig. 3 Example models, illustrating 2×2 design of motor and non-motor difficulty. Motor difficulty was modulated via Block Size (Large vs. Small), and non-motor difficulty via Model Complexity (10 vs. 5 blocks per model)

table contained an equal number of blocks of each type; in other words, each quadrant contained exactly the right blocks to build 1 model (when 10 blocks/model) or 2 models (5 blocks/model). Pilot participants were asked whether they noticed this organization, and none did.

In all variants, participants were instructed to build as quickly and accurately as possible; participants were asked not to scoop or drag blocks across the tabletop, but otherwise received no cues about how to use their hands. If a participant built the model incorrectly, the experimenter asked the participant to double-check whether their model matched the experimenter's model, and the participant had to fix it; this occurred in 1.05% of models (an average of one model every 4 participants). Performance was video recorded.

Outcome measures were: fraction of grasps with DH, and task speed (blocks/second). Each grasp was either DH or NH; because grasping a Lego block is an intrinsically unimanual task, each reach was effectively a two-alternative forced choice (between DH and NH). Task speed was calculated based on the time to complete each model, converted from "time" to "task speed" with x^{-1} to align the direction of both output variables into "higher value = better performance." Task speed was then converted into a "per block" value, to mitigate any simple increases in duration due to varying quantity of blocks.

To assess task speed and fraction of grasps, each video was reviewed by two raters using BORIS event logging software (Friard and Gamba 2016). In cases where the two raters disagreed on any of the participant's left/right choices, or their measurements of any model's start/end time differed by > 1.0 s, the two raters reviewed the video together to reach a consensus. Otherwise, start/end times were averaged between the two raters for each model, and then divided by the number of blocks per model to calculate the task speed. During study preparation, preliminary tests were performed on alternative variants that attempted to modify tactile feedback with different kinds of gloves. In small preliminary samples ($n = 5–15$), these variants did not produce consistent trends toward effects on hand choice; as a result, those variants were not tested or analyzed further.

Precision drawing task

After completing the BBT, participants performed a precision drawing task using both hands, starting with the right dominant hand. Precision drawing performance was measured via the iPad STEGA app (PlatformsSTL, St. Louis, MO, USA). This app has been successfully employed to measure a precision drawing skill (Philip et al. 2023), and is based on a precision drawing task with a history of motor neuroscience research in healthy and clinical populations (Philip and Frey 2014, 2016; Philip et al. 2021). In the STEGA app, participants used an iPad 6th Generation and Apple Pencil (Apple Inc, Cupertino, CA, USA) to draw within the bounds of abstract symmetrical shapes. Each participant completed a total of 30 trials with each hand, comprising 15 shapes at two levels of difficulty each (5–6 mm tolerance). Participants were instructed to complete each shape as quickly as possible while staying within the bounds.

The STEGA app collected raw data at a 50 Hz sampling rate. The raw data included pen position (0.5 mm precision), position and angular errors (deviation from ideal line, measured in mm and degrees respectively), and time (measured in milliseconds). From these raw data, four primary dependent variables were derived: (1) speed (mm/s, mean of each trial), (2) position accuracy (-1 * position error), (3) direction accuracy (-1 * angular error), and (4) velocity smoothness, quantified as a number of the submovements per unit distance (-1 * velocity peaks per shape part) to capture motor performance. These four dependent variables were chosen because they represent movement characteristics that are specialized to the dominant hand (Mutha et al. 2012a).

Data analysis

Data analyses were performed in R version 4.2.1 (R Foundation, Vienna, Austria). To identify which variants modulated hand choice and task speed, we performed a 2 (Block Size: Large, Small) x 2 (Model Complexity: 10, 5 blocks per model) repeated measures ANOVA, separately for each outcome measure. Statistical significance for ANOVAs was detected at $\alpha = 0.025$, based on Bonferroni correction of 0.05/2 for the two outcome measures. Within each ANOVA, the α for each post-hoc test was set via Bonferroni correction based on the number of effects tested.

Secondarily, to determine whether the results of our primary analysis were influenced by covariance between the two outcome measures, we examined the correlation structure between outcome measures, and performed a multivariate linear mixed model (Hadfield 2010) of the effects of Block Size and Model Complexity on both outcome measures together. This model included a random effects term to account for correlations induced by repeated measures (two outcome measures) within individuals.

To compare BBT results with precision drawing performance, we carried out a correlation coefficient analysis between hand usage and the precision drawing variables speed, position accuracy, direction accuracy, and velocity smoothness.

Results

Dominant hand use increased only under the combination of small blocks and high model complexity

We measured the influences on hand usage (fraction of grasps performed with the DH) during the BBT (block building task) with a 2 (Block Size: Small vs. Large) x 2 (Model Complexity: 10 vs. 5 blocks per model) repeated measures ANOVA. We found that hand usage depended on the interaction between Block Size and Model Complexity, as shown in Fig. 4A. Specifically, for the dependent variable of DH usage, we found no significant main effect of Block Size, F (1, 54) = 3.54, $p = 0.0617$, or Model Complexity, F (1, 54) = 0.11, $p = 0.74$. However, we found significant Block Size × Model complexity interaction, F (1, 54) = 10.93, $p = 1.20 \times 10^{-03}$. We adjust alpha-level to 0.0125 for multiple comparisons with Bonferroni correction method in the following post-hoc test. Post-hoc analyses revealed that the interaction effect arose because Block Size had a significant effect on hand usage during high Model Complexity ($p = 4.66\text{x}e^{-05}$, estimated coefficient −0.0471), t (54) = -4.429, but not during low Model Complexity ($p = 0.327$, estimated coefficient 0.0129), t (54) = 0.99. These findings indicate that block size did not matter at low model complexity (5 blocks); but at high model complexity (10 blocks), small blocks led to significantly higher DH usage. In other words, participants used the DH more in the highest-difficulty condition (high model complexity and small blocks) compared to all other conditions.

Task speed decreased only under the high model complexity in both block sizes

We measured the influences on task speed (blocks per second) during the BBT with another 2 × 2 repeated measures ANOVA, identical to the above except for the different outcome variable (task speed). We found that task speed depended on both Block Size, Model Complexity, and their interaction, as shown in Fig. 4B. Specifically, we found significant main effects for Block Size, F (1, 54) = 20.42, $p = 1.19 \times 10^{-05}$; Model complexity, F (1, 54) = 44.09, $p = 4.52 \times 10^{-07}$; and interaction, F (1, 54) = 10.81, $p = 1.24 \times 10^{-03}$. We performed four post-hoc analyses on the interaction effect. We adjust alpha-level to 0.0125 for multiple comparisons with Bonferroni correction method in the following post-hoc test. Our post-hoc examination

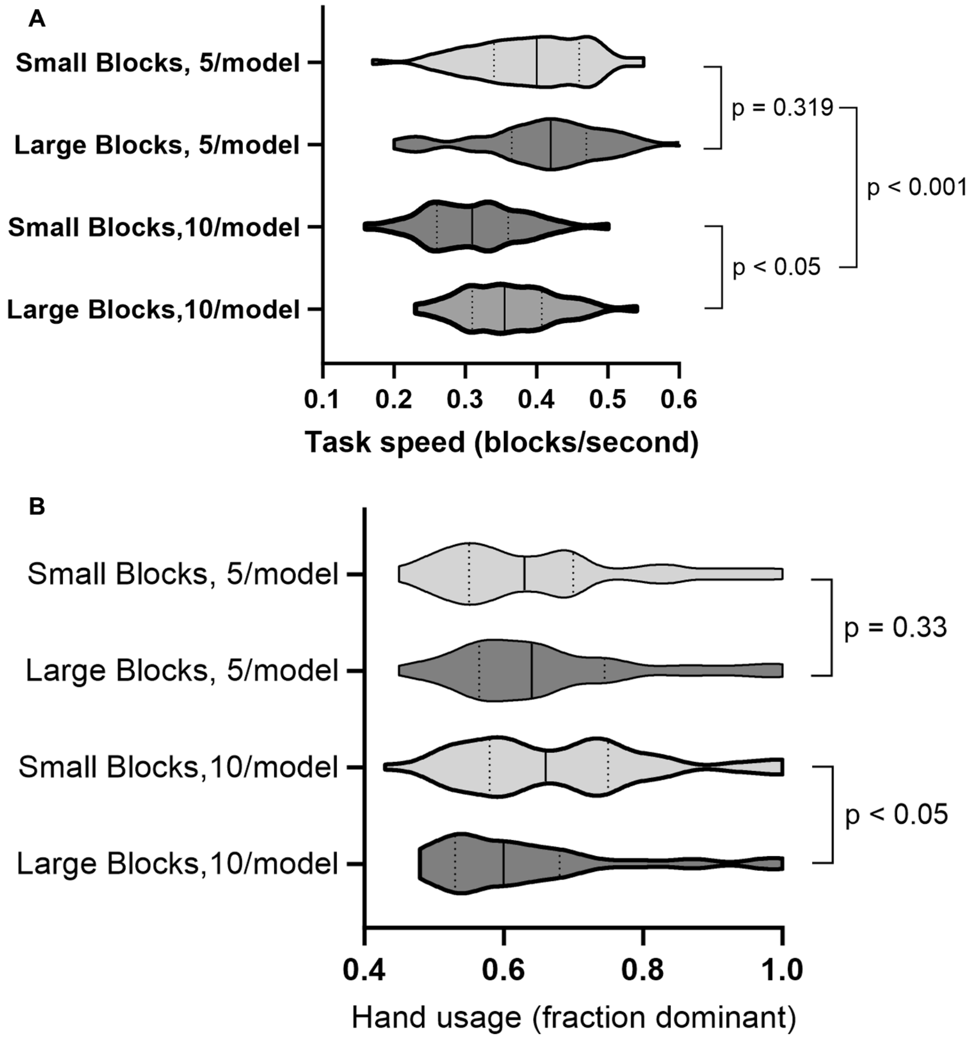

Fig. 4 Effects of Block Size and Model Complexity on hand usage and task speed. **A**: Hand usage showed no main effects, but an interaction effect: DH usage increased only under the combination of small blocks and high complexity (10 blocks/model). **B**: Task speed showed main effects of Block Size and Model Complexity, with an interaction effect such that Block Size only influenced speed under high complexity (10 blocks/model)

of the Block Size effects (main and interaction) revealed that small Block Size was associated with lower task speed during high Model Complexity ($p = 1.12\times e^{-06}$, estimated coefficient of -0.5347, t (54) = -5.485), but not during low Model Complexity ($p = 0.386$, estimated coefficient −0.0843, t (54) = -0.874). Our post-hoc examination of the Model Complexity effects revealed that it had a significant effect on task speed during small Block Size ($p = 2.04\times e^{-10}$, estimated coefficient −0.68, t (54) = -7.804), but not during large Block Size after multiple comparison correction ($p = 0.05$, estimated coefficient −0.2296, t (54) = -2.037). Therefore, increased model complexity induced lower task speed, especially for small blocks.

Block building task performance did not correlate with precision drawing performance

To investigate the relationship between hand usage and hand function, participants completed a precision drawing task with each hand. We examined the correlations between the four BBT variants (2 Block Sizes x 2 Model Complexities) and four behavioral variables from the STEGA precision drawing task (speed, position accuracy, direction accuracy, and velocity smoothness). Contrary to our initial hypothesis, we found no significant correlation between any measure of drawing performance and any BBT variants ($|r| < 0.4$, $p > 0.05$), as shown in Fig. 5.

Covariance between hand usage and task speed did not explain block building task performance

To determine whether our above results were influenced by possible covariance between our outcome measures (hand usage, task speed), we performed a multivariate analysis on the two outcome measures together. Our multivariate linear mixed model identified significant effects of block size (estimated coefficient −0.056, $p < 0.001$), model complexity, (estimated coefficient −0.038, $p = 0.002$) and their interaction (estimated coefficient 0.067, $p < 0.001$). Therefore, both factors still had significant effects on performance,

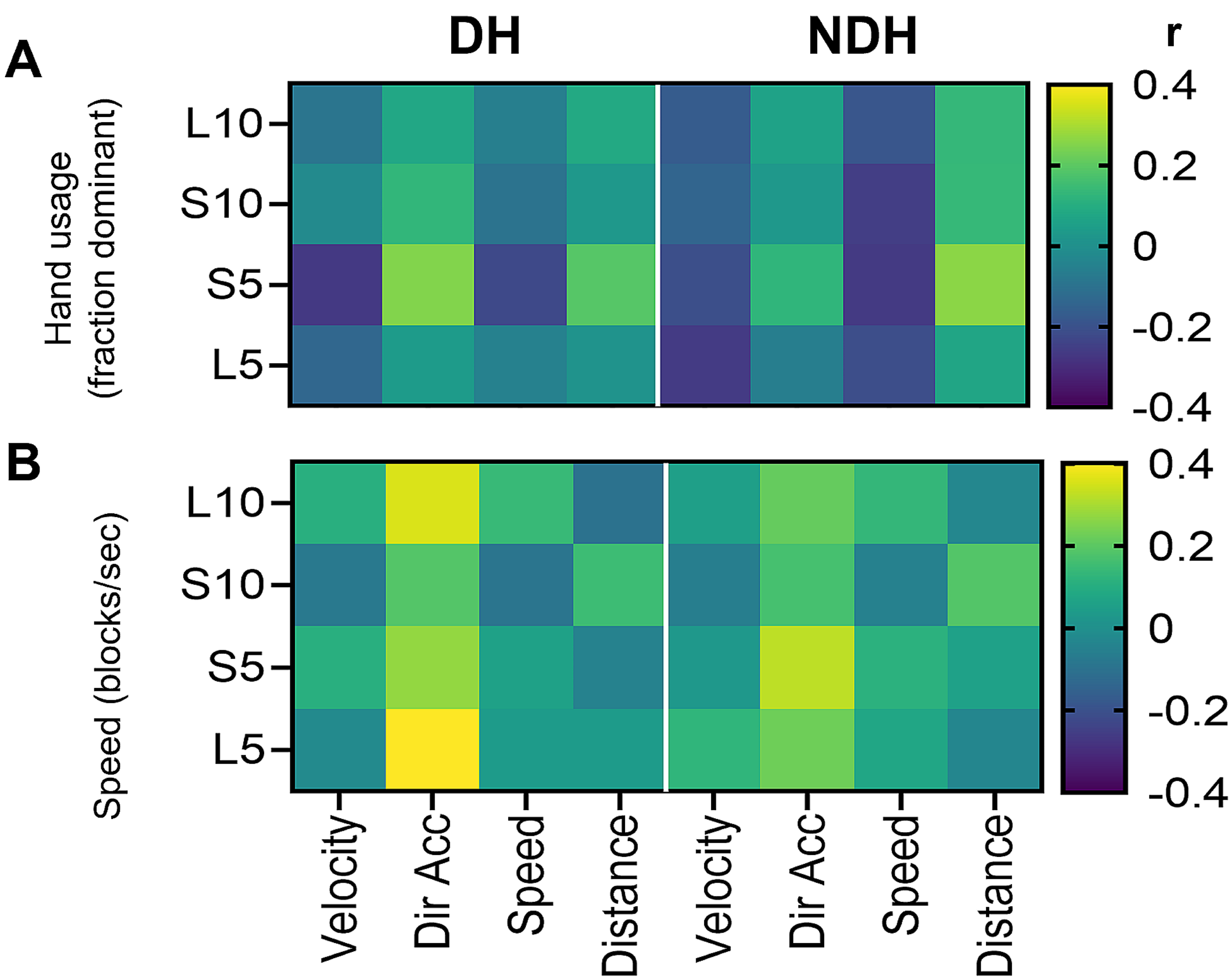

Fig. 5 No significant correlations between precision drawing task and BBT. For each hand (DH and NDH), and all four BBT conditions (rows), none of the four precision drawing variables correlated significantly with (**A**) hand usage or (**B**) task speed

even when analyzing both outcome measures together. Moreover, the two outcome measures were only weakly correlated with each other, $r \leq 0.37$ in all variants, as shown in Fig. 6. Therefore, our results are unlikely to be an artifact of covariance or other interdependence between our outcome measures.

Discussion

The present study represents one of the first systematic attempts to modulate hand usage by controlling the difficulty of an unconstrained reach-to-grasp task. We created and tested new variants of the block building task (BBT) to identify features that could serve as task difficulty axes to modulate hand usage for reach-to-grasp action, and/or hand usage's relationship with motor performance. We found that participant performance (e.g. task speed) responded to both block size (motor difficulty) and model complexity (non-motor difficulty), but hand usage (left/right hand choices) only changed when participants experienced the most difficult combination of these factors – even though participants were instructed to prioritize speed and accuracy, not hand choices. This illustrates the separability of hand performance and choice, and that hand choice preferences in healthy adults are more stable than other aspects of motor behavior.

Increased cognitive-perceptual difficulty led to slower task performance, but only influenced hand usage under high motor difficulty

In the present study, we controlled model complexity to manipulate non-motor difficulty, which we classify as "cognitive-perceptual" difficulty. Greater model complexity should require higher levels of visual-spatial processing

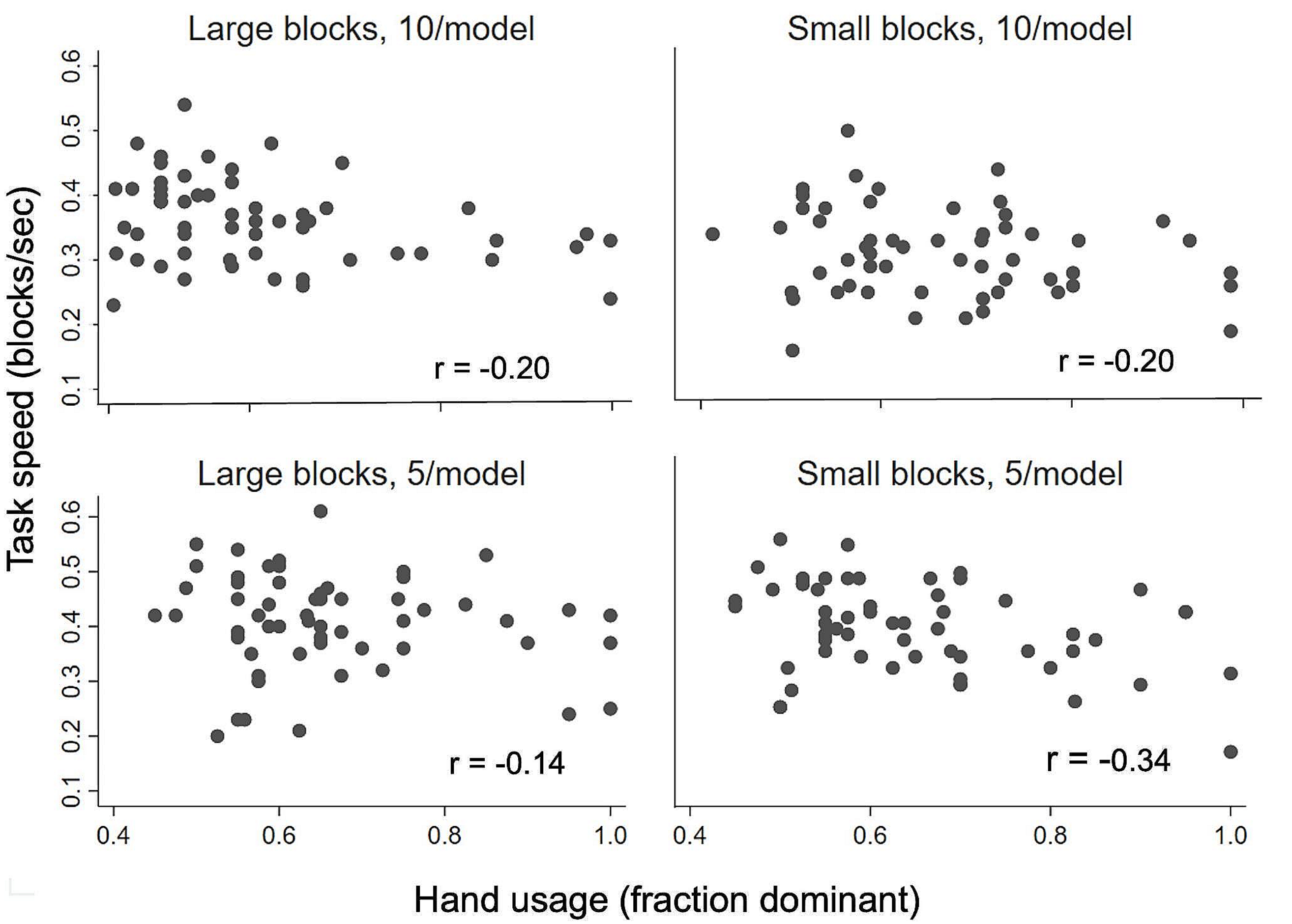

Fig. 6 Hand usage and task speed were only weakly correlated ($r \leq 0.37$), for all variants of the BBT. One outlier in the condition "large blocks, 10/model" not shown (Task speed = 1.11, Hand usage = 0.6); this outlier is also not shown in Fig. 4B.

and working memory to support the (otherwise unchanged) elaborate fine motor skills of building or assembling blocks. Notably, the total number of blocks was identical (40 per condition); high cognitive-perceptual difficulty entailed the participant needing to observe more blocks at a time and build them into a model that contained more blocks. We expected cognitive-perceptual difficulty to influence hand choice because higher-demand cognitive tasks require greater recruitment of cognitive resources such as attention, perception and working memory (Sauseng et al. 2010), and individuals select their dominant hand more frequently as cognitive load increases (Liang et al. 2018b). This phenomenon is thought to reflect cognitive visual-spatial processing in movement, where more complex task demands are associated with greater information processing demands (Rosenbaum 1980; Stelmach 2014), which lead to longer reaction time (Bootsma et al. 2018) and increased use of the dominant hand (Bryden et al. 2011; Liang et al. 2018a, b). However, we found here that increased cognitive-perceptual difficulty in the BBT did not directly affect hand choice. Instead, increased cognitive-perceptual difficulty only led to increased DH use under conditions of high grasp motor difficulty.

Negative results are sometimes difficult to interpret, but our multiple task variants and outcome variables allow us to rule out a number of alternatives. Conceivably, our cognitive-perceptual manipulation could have been insufficient to affect participant behavior; however, our cognitive-perceptual manipulation (model complexity) always affected movement speed. Alternatively, it is conceivable that our negative result arose as an artifact of statistical thresholds; however, this interpretation is unlikely given the different direction of the model-complexity effect at each block size (compare two slopes in Fig. 4A). One uncertainty cannot be resolved by our current data: the interaction between motor and non-motor difficulty may be specific to the combination of those two factors or may represent a simpler "total difficulty" effect.

Regardless of the source of our difficulty effect, it had a greater impact on task performance (task speed) rather than hand usage, despite instructions to the contrary: participants were instructed to move quickly and accurately, but their instructions avoided any mention of hand choice. ("Accuracy" at the BBT effectively also means task speed: participants continued the task until they completed all movements, so movement errors would introduce delays as the participant made additional corrective actions.) This extends previous findings about the stability of hand choice: we have previously shown that people avoid *decreasing* DH use even when it would be useful to do so (Philip et al. 2022a), but here we demonstrate that people also avoid *increasing* DH use.

Motor difficulty effects could depend on grasping itself or the post-grasping task

We found that motor difficulty (block size) affected hand choice and task speed during conditions of high model complexity (10 blocks per model). This interaction effect has been discussed in the previous section, but it is important to briefly discuss the effects of block size on their own. Previous studies had found that DH use was increased by more difficult post-grasp actions, but not by more difficult grasp itself (Mamolo et al. 2004; Leconte and Fagard 2006; Bryden et al. 2011). A limitation of the BBT is that it is difficult to separate these two types of motor difficulty: because the BBT presents a context in which reach-to-grasp actions occur as part of an unconstrained goal-directed task, smaller blocks have two effects: they increase difficulty of the initial grasp and also the subsequent model-building. Future studies could disambiguate this by quantifying hand usage during the model-building phase of the BBT, where we would expect a stronger effect of block size. Given the prior research, it seems likely that the current data's motor difficulty interaction effect arose primarily from difficulty in the post-grasp task (i.e. model building).

Hand choices did not correlate with precision drawing performance

We found no relationships between hand choices and precision drawing performance, for any version of the BBT or any precision drawing variable. In other words, our data did not support our hypothesis that participants with better NDH control would be more willing to use their NDH. This could potentially because the two tasks were not well aligned: reach-to-grasp performance may be unrelated to precision endpoint (drawing) control performance. Indeed, these two tasks have separable performance characteristics (Pacilli et al. 2014; Israely and Carmeli 2017). For example, even if individuals with better NDH drawing performance are more likely to use that hand for fine manipulation, this might not affect their reach-to-grasp choices. Future studies should pair the BBT with other tests of manual dexterity to assess other aspects of motor performance. With our current measures, our precision drawing data support the idea that left/right hand choices for reaching do not depend on fine endpoint control capacity among healthy adults. This is consistent with our other data showing that hand usage is poorly correlated with task performance even within the same reach-to-grasp task.

Why do people rely on their dominant hand for ordinary or difficult tasks?

It is widely assumed that people favor their DH for everyday activities because of the DH's performance advantages in numerous aspects of motor control (Corey et al. 2001; Bagesteiro and Sainburg 2002; Mutha et al. 2012b; Przybyla et al. 2013). Under this framework, there are many possible mechanisms by which BBT difficulty could increase DH use. For example, difficult tasks might increase DH use via a speed/stability tradeoff: it takes additional time to encode a complex movement plan, which could drive individuals to use their DH for more accuracy and stability (Wolpert and Landy 2012). Or, more simply, difficult tasks could entail an accuracy demand that drives the use of the hand that provides greater accuracy and speed for grasp (Flindall et al. 2014), manipulation (Stone et al. 2013), and the planning thereof (Janssen et al. 2011). Alternatively, high-difficulty situations could increase individuals' reliance on tactile feedback for manipulation, which is known to drive DH use (Stone and Gonzalez 2015); or high-difficulty situations could exceed the endurance of the NH. These four explanations are neither exhaustive nor mutually exclusive, but they are not sufficient. Motor function and task demands surely play a role in hand choices, but cannot provide a complete explanation for human hand choice behavior (Bryden 2016). Indeed, hand choices can be separated from performance asymmetries: when injuries make people more dexterous with their NH than their DH, they nevertheless continue to favor their now-less-dexterous DH (Philip et al. 2022a).

Hand choice is a complex phenomenon that is driven not only by motor factors, but also by psychological and personal factors. Such factors include reinforcement history and confidence (Stoloff et al. 2011), habit (Kim et al. 2020), expected effort (Schweighofer et al. 2015), and cultural pressures (Lee-Feldstein and Harburg 1982; Papadatou-Pastou et al. 2020). To fully understand hand choice behavior, future studies must identify the psychological, emotional, and other personal factors that interact with motor asymmetries to drive hand choices.

Conclusion

In this study, we used Block Building Task to identify the effects of motor and non-motor difficulty on hand usage for reach-to-grasp actions. We found that hand usage (left/right hand choices) was relatively insensitive to task difficulty: participants increased the use of their dominant hand only for the most difficult combination of conditions, even though both motor and non-motor difficulty influenced task performance (task speed). Hand usage was independent from performance of the reach-to-grasp task, or performance at a precision drawing task. These results demonstrate the stability of left/right hand choices in healthy adults, even against increased use of the dominant hand. Participants were told to prioritize performance speed, but nevertheless sacrificed task speed in favor of maintaining a consistent ratio of left/right hand choices across the workspace.

In conclusion, we found that individuals tend to rely more on their dominant hand when faced with multifaceted difficulties, making hand dominance switching less easily achievable, especially as tasks become more challenging. This extends previous findings about the stability of hand choices: patients with chronic peripheral injury avoid *decreasing* DH use (Philip et al. 2022a), and here we found that people also avoid *increasing* DH use. In this context, our results suggest that – for patients who would benefit from increased use of the non-dominant hand after DH impairment – increased difficulty with daily activities will not suffice to promote beneficial compensatory use of the NDH. Instead, effective remediation strategies should be developed to explicitly promote dominance switching to enhance the use of the less-affected arm.

Acknowledgements This work was funded by NIH/NINDS R01 NS114046 to BAP. The authors would like to thank Summer Fletcher for their help with data collection; and Xinye Wu, Jackie Hardy, Summer Fletcher, Delaney McIntyre, Tina Nguyen, Rachel Graves, and Elizabeth Magee for their help with video coding.

Declarations

Dr. Philip and Washington University in St. Louis have a licensing agreement with PlatformSTL to commercialize the iPad app used in this study.

References

Bagesteiro LB, Sainburg RL (2002) Handedness: dominant arm advantages in control of limb dynamics. J Neurophysiol 88:2408–2421

Baumard J, De Sousa E, Roy V, Deschamps L, Iodice P, Osiurak F, Brisson J (2023) Grip selection without tool knowledge: end-state comfort effect in familiar and novel tool use. Exp Brain Res 241:1989–2000. https://doi.org/10.1007/s00221-023-06655-0

Bootsma JM, Hortobágyi T, Rothwell JC, Caljouw SR (2018) The role of task difficulty in learning a visuomotor skill. Med Sci Sports Exerc 50:1842–1849

Bryden PJ (2016) The influence of M. P. Bryden's work on lateralization of motor skill: is the preferred hand selected for and better at tasks requiring a high degree of skill? Laterality 21:312–328. https://doi.org/10.1080/1357650X.2015.1099661

Bryden PJ, Mayer M, Roy EA (2011) Influences of task complexity, object location, and object type on hand selection in reaching in left and right-handed children and adults. Dev Psychobiol 53:47–58. https://doi.org/10.1002/dev.20486

Corey DM, Hurley MM, Foundas AL (2001) Right and left handedness defined: a multivariate approach using hand preference and hand performance measures. Cogn Behav Neurol 14:144–152

Flindall JW, Doan JB, Gonzalez CLR (2014) Manual asymmetries in the kinematics of a reach-to-grasp action. Laterality 19:489–507. https://doi.org/10.1080/1357650X.2013.862540

Friard O, Gamba M (2016) BORIS: a free, versatile open-source event-logging software for video/audio coding and live observations. Methods Ecol Evol 7:1325–1330

Gabbard C, Rabb C (2000) What determines choice of limb for unimanual reaching movements? J Gen Psychol 127:178–184

Gonzalez CL, Goodale MA (2009) Hand preference for precision grasping predicts language lateralization. Neuropsychologia 47:3182–3189

Gonzalez CLR, Ganel T, Goodale MA (2006) Hemispheric specialization for the visual control of action is independent of handedness. J Neurophysiol 95:3496–3501. https://doi.org/10.1152/jn.01187.2005

Gonzalez CL, Whitwell RL, Morrissey B, Ganel T, Goodale MA (2007) Left handedness does not extend to visually guided precision grasping. Exp Brain Res 182:275–279. https://doi.org/10.1007/s00221-007-1090-1

Hadfield JD (2010) MCMC methods for multi-response generalized linear mixed models: the MCMCglmm R package. J Stat Softw 33:1–22

Harris PA, Taylor R, Thielke R, Payne J, Gonzalez N, Conde JG (2009) Research electronic data capture (REDCap)—a metadata-driven methodology and workflow process for providing translational research informatics support. J Biomed Inform 42:377–381. https://doi.org/10.1016/j.jbi.2008.08.010

Israely S, Carmeli E (2017) Handwriting performance versus arm forward reach and grasp abilities among post-stroke patients, a case-control study. Top Stroke Rehabil 24:5–11. https://doi.org/10.1080/10749357.2016.1183383

Janssen L, Beuting M, Meulenbroek R, Steenbergen B (2009) Combined effects of planning and execution constraints on bimanual task performance. Exp Brain Res 192:61–73. https://doi.org/10.1007/s00221-008-1554-y

Janssen L, Meulenbroek RGJ, Steenbergen B (2011) Behavioral evidence for left-hemisphere specialization of motor planning. Experimental Brain Res Experimentelle Hirnforschung Expérimentation cérébrale 209:65–72. https://doi.org/10.1007/s00221-010-2519-5

Kim S, Han CE, Kim B, Winstein CJ, Schweighofer N (2020) Arm choice post-stroke is habitual rather than optimal in right-, but not in left-paretic individuals. medRxiv:2020.2008. 2031.20185389

Klein LK, Maiello G, Fleming RW, Voudouris D (2021) Friction is preferred over grasp configuration in precision grip grasping. J Neurophysiol 125:1330–1338

Leconte P, Fagard J (2006) Which factors affect hand selection in children's grasping in hemispace? Combined effects of task demand and motor dominance. Brain Cogn 60:88–93. https://doi.org/10.1016/j.bandc.2005.09.009

Lee-Feldstein A, Harburg E (1982) Alcohol use among right-and left-handed persons in a small community. J Stud Alcohol 43:824–829

Liang J, Wilkinson K, Sainburg RL (2018a) Is hand selection modulated by cognitive–perceptual load? Neuroscience 369:363–373

Liang J, Wilkinson KM, Sainburg RL (2018b) Cognitive-perceptual load modulates hand selection in left-handers to a greater extent than in right-handers. Exp Brain Res 237:389–399. https://doi.org/10.1007/s00221-018-5423-z

Mamolo CM, Roy EA, Bryden PJ, Rohr LE (2004) The effects of skill demands and object position on the distribution of preferred hand reaches. Brain Cogn 55:349–351. https://doi.org/10.1016/j.bandc.2004.02.041

Mani S, Mutha PK, Przybyla A, Haaland KY, Good DC, Sainburg RL (2013) Contralesional motor deficits after unilateral stroke reflect hemisphere-specific control mechanisms. Brain 136:1288–1303

Mutha PK, Haaland KY, Sainburg RL (2012a) The effects of brain lateralization on motor control and adaptation. J Mot Behav 44:455–469

Mutha PK, Haaland KY, Sainburg RL (2012b) The effects of brain lateralization on motor control and adaptation. J Mot Behav 44:455–469. https://doi.org/10.1080/00222895.2012.747482

Oldfield RC (1971) The assessment and analysis of handedness: the Edinburgh inventory. Neuropsychologia 9:97–113

Pacilli A, Germanotta M, Rossi S, Cappa P (2014) Quantification of age-related differences in reaching and circle-drawing using a robotic rehabilitation device. Appl Bionics Biomech 11:91–104

Papadatou-Pastou M, Ntolka E, Schmitz J, Martin M, Munafo MR, Ocklenburg S, Paracchini S (2020) Human handedness: a meta-analysis. Psychol Bull 146:481–524. https://doi.org/10.1037/bul0000229

Paulun VC, Kleinholdermann U, Gegenfurtner KR, Smeets JB, Brenner E (2014) Center or side: biases in selecting grasp points on small bars. Exp Brain Res 232:2061–2072. https://doi.org/10.1007/s00221-014-3895-z

Philip BA, Frey SH (2014) Compensatory changes accompanying chronic forced use of the nondominant hand by unilateral amputees. J Neurosci 34:3622–3631

Philip BA, Frey SH (2016) Increased functional connectivity between cortical hand areas and praxis network associated with training-related improvements in non-dominant hand precision drawing. Neuropsychologia 87:157–168

Philip BA, Kaskutas V, Mackinnon SE (2020) Impact of handedness on disability after unilateral upper-extremity peripheral nerve disorder. Hand 15:327–334

Philip BA, McAvoy MP, Frey SH (2021) Interhemispheric parietal-frontal connectivity predicts the ability to acquire a nondominant hand skill. Brain Connect 11:308–318

Philip BA, Thompson MR, Baune NA, Hyde M, Mackinnon SE (2022a) Failure to compensate: patients with nerve Injury Use their injured Dominant Hand, even when their nondominant is more dexterous. Arch Phys Med Rehabil 103:899–907. https://doi.org/10.1016/j.apmr.2021.10.010

Philip BA, Thompson MR, Baune NA, Hyde M, Mackinnon SE (2022b) Failure to compensate: patients with nerve Injury Use their injured Dominant Hand, even when their nondominant is more dexterous. Arch Phys Med Rehabil 103:899–907

Philip BA, Li F, Hawkins-Chernof E, Chen L, Swamidass V, Zwir I (2023) Motor Assessment with the STEGA iPad app to measure handwriting in children. Am J Occup Therapy 77:7703205010

Przybyla A, Coelho CJ, Akpinar S, Kirazci S, Sainburg RL (2013) Sensorimotor performance asymmetries predict hand selection. Neuroscience 228:349–360. https://doi.org/10.1016/j.neuroscience.2012.10.046

Randerath J, Li Y, Goldenberg G, Hermsdörfer J (2009) Grasping tools: effects of task and apraxia. Neuropsychologia 47:497–505. https://doi.org/10.1016/j.neuropsychologia.2008.10.005

Rosenbaum DA (1980) Human movement initiation: specification of arm, direction, and extent. J Exp Psychol Gen 109:444

Sainburg RL (2002) Evidence for a dynamic-dominance hypothesis of handedness. Exp Brain Res 142:241–258

Sauseng P, Griesmayr B, Freunberger R, Klimesch W (2010) Control mechanisms in working memory: a possible function of EEG theta oscillations. Neurosci Biobehavioral Reviews 34:1015–1022

Scharoun SM, Scanlan KA, Bryden PJ (2016) Hand and grasp selection in a preferential reaching task: the effects of object location, orientation, and task intention. Front Psychol 7:360

Schweighofer N, Xiao Y, Kim S, Yoshioka T, Gordon J, Osu R (2015) Effort, success, and nonuse determine arm choice. J Neurophysiol 114:551–559

Stelmach GE (2014) Information processing in motor control and learning. Academic

Stoloff RH, Taylor JA, Xu J, Ridderikhoff A, Ivry RB (2011) Effect of reinforcement history on hand choice in an unconstrained reaching task. Front Neurosci 5:41. https://doi.org/10.3389/fnins.2011.00041

Stone KD, Gonzalez CL (2014) Grasping with the eyes of your hands: hapsis and vision modulate hand preference. Exp Brain Res 232:385–393. https://doi.org/10.1007/s00221-013-3746-3

Stone KD, Gonzalez CL (2015) Manual preferences for visually- and haptically-guided grasping. Acta Psychol (Amst) 160:1–10. https://doi.org/10.1016/j.actpsy.2015.06.004

Stone KD, Bryant DC, Gonzalez CL (2013) Hand use for grasping in a bimanual task: evidence for different roles? Exp Brain Res 224:455–467. https://doi.org/10.1007/s00221-012-3325-z

Voudouris D, Smeets JB, Brenner E (2012) Do humans prefer to see their grasping points? J Mot Behav 44:295–304. https://doi.org/10.1080/00222895.2012.703975

Wojtkiewicz DM, Saunders J, Domeshek L, Novak CB, Kaskutas V, Mackinnon SE (2015) Social impact of peripheral nerve injuries. Hand 10:161–167

Wolpert DM, Landy MS (2012) Motor control is decision-making. Curr Opin Neurobiol 22:996–1003. https://doi.org/10.1016/j.conb.2012.05.003