Independent Influences of Movement Distance and Visual Distance on Fitts' Law

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Abstract

Fitts' Law is among a handful of psychophysical laws. However, one of the fundamental variables of Fitts' Law – the movement distance, D – confounds two variables: the physical distance the effector has to move to reach a goal, and the visually perceived distance to that goal. While these two quantities are functionally equivalent in typical motor behaviors, decoupling them might improve our understanding of Fitts' Law. Here we leveraged the phenomenon of visuomotor gain adaptation to de-confound movement and visual distance during goal-directed upper-limb movements. We found that movement distance and visual distance can influence movement times, supporting a variant of Fitts' Law that considers both. The weighting of movement versus visual distance was modified by restricting movement range (emphasizing vision) or degrading visual feedback (emphasizing proprioception). These results reflect a multisensory integration process in the computation of expected movement difficulty, perhaps during early stages of motor planning.

Keywords: adaptation; Fitt's Law; speed-accuracy tradeoff; motor behavior; skill; skill learning

Public Significance

You will automatically slow your movement when picking up a needle five inches away versus a handkerchief three inches away. This fact is elegantly formalized by Fitts' Law, which mathematically relates movement duration to movement difficulty. However, one of the fundamental variables in the law – the distance of a planned movement – is ambiguous: Is it the actual distance the hand has to move that shapes planning and biases movement duration, or is it the visually perceived distance? We decoupled these variables, finding that Fitts' Law is shaped by both quantities, and that the influence of one versus the other is related to the relevance of proprioceptive versus visual information. We believe our "addendum" to Fitts' Law is timely, as everyday motor behavior has become increasingly enmeshed with virtual environments that abstract our movements into digital realities.

Introduction

Motor behavior is limited by a speed-accuracy trade-off: whenever an action must be executed quickly, its accuracy diminishes. Such a trade-off has been observed in saccadic eye movements (Gopal et al., 2017; Wu et al., 2010), goal-directed reaches (Goldberg et al., 2015), pointing movements (van Donkelaar, 1999), and even video game performance (Listman et al., 2021; Warburton et al., 2023). Fitts (1954) famously formalized the relationship between movement speed and accuracy constraints. This relationship, known as Fitts' Law, is one of the few so-called "laws" of psychophysics and has been replicated (and occasionally caveated) extensively over decades of behavioral research in humans and other animals (Adam, 1992; de Grosbois et al., 2015; Goldberg et al., 2015; Gopal et al., 2017; MacKenzie, 1992; MacKenzie & Buxton, 1992; Sambrooks & Wilkinson, 2013; Van Gisbergen et al., 1981; Wu et al., 2010).

The common form of Fitts' Law states that movement duration (MT) is logarithmically related to the width of a movement target (W) and the movement's amplitude (D):

$$MT = a + b * \log_2(2D/W)$$

where *a* and *b* are empirically-determined free parameters. The quantity $\log_2(2D/W)$ is typically referred to as the Index of Difficulty (ID), reflecting a task's accuracy constraints (other accuracy constraints, such as the weight of a held tool, can be incorporated as well).

Fitts' Law has been of particular interest in applications involving human-computer interactions (MacKenzie, 1992), such as controlling a cursor on a computer screen with a mouse (Sambrooks & Wilkinson, 2013; Thompson et al., 2004; Whisenand & Emurian, 1996), making movements in virtual or augmented reality (Rohs et al., 2011; Rohs & Oulasvirta, 2008), or performing actions in a video game (Listman et al., 2021; Warburton et al., 2023). In these virtual arenas, the inherent ambiguity of the movement amplitude (*D*) term of Fitts' Law is laid bare: Does *D* reflect the physical distance traversed by the limb, or the perceptual distance over which one intends to move a proxy of their action (e.g., a cursor or avatar)? For example, a hand-held computer mouse only needs to move a few centimeters for its visual proxy to traverse a large computer monitor. It has been observed that as visual distance on a screen becomes increasingly decoupled from physical movement distance, predictions using Fitts' Law tend to be degraded (Thompson et al., 2004).

Popular explanations for Fitts' Law suggest that it is an outgrowth of basic facets of the motor system. For instance, it has been argued that Fitts' Law emerges from the size of the command signal used to produce a movement – a smaller command signal may achieve greater accuracy but result in a slower movement, while a larger command signal may generate a faster but less accurate movement. This "signal-dependent noise" model (Harris & Wolpert, 1998) suggests that movement times (MTs) primarily reflect the physical distance traversed by the limb executing the movement.

It has also been argued that Fitts' Law emerges in the absence of such variability. Al Borno and colleagues (2020) position Fitts' Law at a more abstract level of planning: When a task is challenging, action selection is more likely to land upon an inefficient solution in the repertoire of potential reaches of varying movement durations that land within the target region, resulting in accurate but slower movements; however, when accuracy constraints are relaxed, more potential movement policies are readily selected with shorter movement durations, but more variable endpoints. If Fitts' Law emerges at this more abstract level (action selection), rather than as a direct consequence of the command signal itself, movement durations could be affected by multiple factors that influence planning. To this effect, some have observed violations of Fitts' Law when visual illusions alter the perception of movement amplitude (D) and/or the width of a goal target (W), suggesting that perceptual representations alone can shape speed-accuracy tradeoffs during movement planning (van Donkelaar, 1999, but see also Alphonsa et al., 2016).

Here we hypothesized that Fitts' Law is influenced by both visual and physical movement distances. To test this, we leveraged the phenomenon of visuomotor gain adaptation (Krakauer et al., 2004) to decouple movement and visual distance. We found support for our predictions in a standard reaching task with continuous visual feedback: MTs were influenced by both movement and visual distance even when no visual feedback was provided (Exp. 1). Moreover, the relative weighting of these quantities was flexible: Visual distance dominated when the range of physical movements was restricted (Exp. 2). In contrast, when continuous visual feedback was removed during adaptation, enhancing the role of proprioceptive input, movement distance alone could explain MTs (Exp. 3). These latter effects persisted when we accounted for difficulty differences between conditions attributable to latent task geometry (Exp. 4). Taken together, our results suggest that Fitts' Law may reflect an integration of multiple sensory inputs, namely vision and proprioception. We speculate that this process may occur during an early planning stage of goal-directed movement.

Methods

Participants

Experiments 1 & 4a were conducted in-lab. A total of N = 20 subjects (19 right-handed, age: 28.9 ± 9.1, 55% female) participated in these experiments at an honorarium of $10/hr (Exp. 1: N=10, age: 29.8 ± 10.9, 50% female; Exp. 4a: N=10, age: 27.9 ± 7.5, 60% female). (Sample sizes for Experiments 1 and 4a were not determined using *a priori* power analysis, though are consistent with similar investigations of the basic psychophysics of Fitts' Law; Alphonsa et al., 2016; Rohs et al., 2011; Rohs & Oulasvirta, 2008; van Donkelaar, 1999; Wu et al., 2010). All participants provided informed, written consent in accordance with procedures approved by the Yale University Institutional Review Board, and reported their handedness using the Edinburgh Handedness Inventory, with a score of >40 indicating right-handedness (Oldfield, 1971).

Experiments 2, 3, and 4b were crowd-sourced, where data from N = 84 subjects (77 right-handed, 7 ambidextrous, age: 28.3 ± 4.6, 54% female) was collected online via Prolific (Exp. 2: N=27, age: 27.1 ± 5.0, 56% female; Exp. 3: N=27, age: 29.2 ± 4.7, 52% female; Exp. 4b: N=30, age: 28.5 ± 4.1, 53% female). Recruitment was restricted to right-handed or ambidextrous individuals in the United States between the ages of 18 and 35, who had at least 40 prior Prolific submissions, and a sample size of 30 was targeted for each experiment. While not based on *a priori* power analysis, this sample size vastly exceeds typical psychophysics sample sizes.

Apparatus

In-lab participants sat on a height-adjustable chair facing a 24.5-in. LCD monitor (Asus VG259QM; display size: 543.74 mm x 302.62 mm; resolution: 1920 x 1080 pixels; frame rate set to 240Hz; 1 ms response time), positioned horizontally ~30 cm in front of the participant above the table platform, thus preventing vision of the hand. In their dominant hand they held a stylus embedded within a custom-modified paddle which they could slide across a digitizing tablet (Wacom PTH860; active area: 311 mm x 216 mm). Hand position was recorded from the tip of the stylus sampled by the tablet at 200 Hz. Stimulus presentation and movement recording were controlled by a custom-built Octave script (GNU Octave v5.2.0; Psychtoolbox-3 v3.0.18; Ubuntu 20.04.4 LTS).

General Task Protocol

Across all experiments, participants completed center-out reaching movements and were instructed to move their hand (in-lab, **Figure 1a**) or computer mouse (online) to land a displayed cursor within a visually indicated target. Participants were instructed to always move as quickly and accurately as possible. A trial would start when participants brought their cursor to the central starting location (in-lab: 7mm diameter starting circle; online: 6mm diameter). To assist with re-centering, the cursor (in-lab: 3mm diameter cursor; online: 4mm diameter) was visually displayed when it was within 1cm of the start location. After waiting in the center for 500ms, a circular target would appear at one of three possible angular locations (straight ahead, or ±45° from straight ahead) and two possible distances (in-lab: 5.3cm or 10.6cm away from the start location; online: 4cm or 8cm away). For online studies, mouse acceleration was inhibited by our task code.

We leveraged gain perturbations (Krakauer et al., 2004) – alterations in the relationship between movement distance and the visual consequences of those movements – to decouple physical and visual distance in “mini-blocks” of trials. We used a 2 X 2 design that yielded 4 possible conditions (**Figure 1b**): 1) the target was displayed at the shorter distance, and the required movement was similarly short (gain = 1; no perturbation), 2) the target was displayed at the farther distance, and the required movement was similarly long (gain = 1), 3) the target was displayed at the shorter distance but the required movement displacement was the same as the longer distance (gain = 0.5), 4) the target was displayed at the farther distance, but the required movement displacement was the same as the shorter distance (gain = 2). In-lab participants would have to physically move either 5.3cm or 10.6cm for all respective trials, whereas online participants executed dramatically shorter movement amplitudes due to their use of a computer mouse or trackpad. Trials ended when participants stopped moving (velocity criterion: <5mm/s for greater than 200ms) or after a maximum time elapsed from the start of their reach. In Experiments 1 and 2, this maximum time was 1s. In Experiments 3 and 4, this maximum time was 2s.

In each mini-block (**Figure 1c**), participants first completed an “adaptation phase” (Exps. 1 & 2: 12 trials; Exps. 3 & 4: 21 trials), in which visual feedback was provided. If the visual cursor successfully landed within the target region, participants received 10 points, which was displayed adjacent to the target in green text and added to a point total displayed on the screen. Endpoint cursor feedback and points were displayed for 500ms. This adaptation phase allowed participants to learn the appropriate distances required to hit the target for each condition (i.e., to undergo gain adaptation). After adaptation, participants completed a “test phase” (all Exps.: 6 trials), in which, critically, no visual feedback nor points were provided. All key movement time (MT) analyses were performed on these testing phases to preclude effects of feedback corrections. During the testing phases, participants were instructed to try to recreate the movements that were successful in the previous trials, and were informed that they would not receive any feedback about their performance.

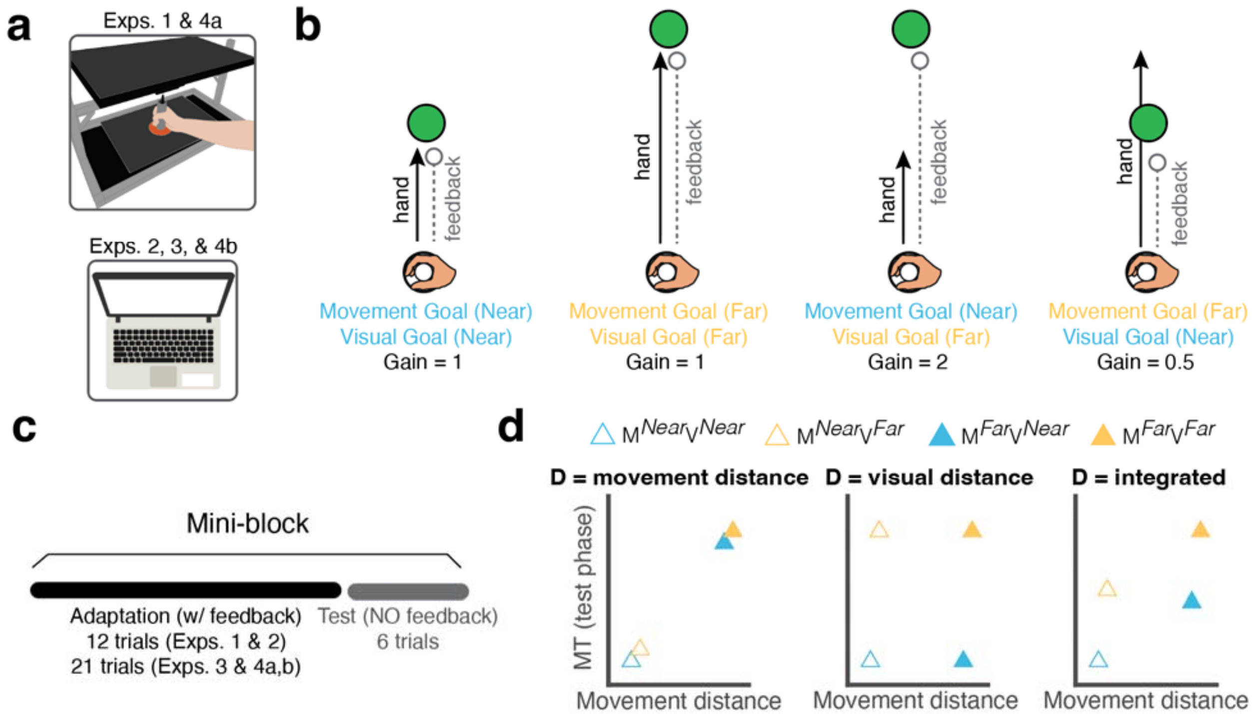

Figure 1. *Task design and theoretical predictions*. **a)** *Top:* In-lab experimental apparatus in Exps. 1 and 4A. Participants made center-out reaching movements on a digitizing tablet and viewed visual feedback on a monitor that occluded the arm. *Bottom*: Exps. 2, 3, and 4B were conducted online. **b)** Illustration of the four conditions used across all experiments – a 2x2 design crossing two levels of movement goal distances and visual goal distances by using feedback gain perturbations. **c)** Participants completed multiple mini-blocks for each of the four conditions. These mini-blocks consisted of a short adaptation phase with feedback, followed by a no-feedback test phase. Analyses were conducted on movement time (MT) in the test phase. **d)** Idealized predicted movement times given different (log) movement distances across the four conditions, for three different models. The models differ in their definition of the D term of Fitts' Law.

Left: movement distance (MD model); *Center*: visual distance (VD model); *Right:* multi-sensory integration of both movement and visual distance (MSI model).

Experiment 1

Participants (N=10) were provided continuous ("online") cursor feedback during the adaptation phase of each mini-block. For trials where the visual distance and the movement distance were identical (gain = 1), the cursor veridically tracked the position of the hand. For trials where the visual distance and the movement distance were de-confounded (**Figure 1b**), the cursor was perturbed (i.e., for the condition in which the visual distance was twice as long as the movement distance, a hand displacement of 1 cm resulted in a cursor displacement of 2 cm). This manipulation is typically referred to as a gain perturbation (Krakauer et al., 2004), and the ratio between the visual distance and the movement distance is referred to as the gain (i.e., the previous example has gain = 2). Training mini-blocks were 12 trials in length, followed by a 6-trial test phase. Participants completed 24 training-test mini-block pairs, with 6 pairs for each condition. Conditions were pseudo-randomized such that all 4 conditions appeared in a shuffled order before repeating in a new shuffled order. The target diameter was 1.4cm and reach distances were 5.3cm or 10.6 cm.

Experiment 2

Participants (N=27) completed a task that was largely identical to Exp. 1. The task was slightly shorter in length (16 training-test mini-block pairs; 4 per condition) to accommodate the crowd-sourced format. The target diameter was 1.6cm and visual distances were 4cm or 8cm (assuming a standard of 72 pixels per inch). Crucially, given the online format, the task now required only small, restricted mouse movements.

Experiment 3

Participants (N=27) completed a similar task to Exp. 2, with some modifications. Instead of providing online feedback during the adaptation phase, feedback was degraded such that it was only provided when participants stopped moving (i.e., endpoint-only feedback). Since adaptation to endpoint feedback is slower (Taylor et al., 2014), adaptation phases were lengthened to 21 trials. Participants completed 16 training-test mini-block pairs (4 per condition). The endpoint cursor seen during adaptation followed the 2 X 2 gain perturbation design employed in Exps. 1 and 2 (**Figure 1b**). Additionally, to facilitate learning in this more difficult context, the targets were slightly larger (2cm diameter) and color-coded: blue targets indicated no gain manipulation, green targets indicated that participants needed to “go farther” than expected in order for the cursor to hit the target, and red targets indicated that participants needed to “stop shorter” than expected in order to hit the target. This instruction was repeated throughout the task at the start of each training mini-block and there was an additional 3-trial tutorial used to explain the nature of the perturbations. The target diameter was 2cm and reach distances were 4cm or 8cm.

Experiments 4a and 4b

Experiments 4a (in-lab, N=10) and 4b (online, N=30) were largely identical to Exp. 3, including the 3-trial tutorial, color-coded targets, and endpoint-only feedback. Participants completed 16 training-test mini-block pairs (4 per condition) and adaptation phases were again 21 trials long. The target diameter was 2cm and reach distances were 4cm or 8cm. However, in Exp. 4, the cursor was not manipulated using a “gain” manipulation. Instead, Exp. 4 aimed to preserve the “effective width” of the target across all 4 conditions. By effective width, we refer to the fact that gain manipulations will alter the area that constitutes successful reaches which would cause the cursor to land in the target. In other words, if the gain is 2 and a far target distance is displayed, any initial small deviation from the correct amplitude or angle of the reach, relative to the goal, will be magnified two-fold by the visually displayed cursor. Thus, in effect, the region which allows successful reaches to land within the targets has effectively half the radius as the equivalent (in movement distance) no-gain condition.

To control for this geometric difficulty difference, Exp. 4 employed a slightly modified perturbation: In conditions where the visual and movement distance were matched, no change occurred, as in earlier experiments. However, in conditions where the movement distance was decoupled from visual distance, endpoint feedback was calculated using a novel translation that accounted for effective width (a “difficulty clamp”). That is, if the movement distance exceeded the visual distance of the target, the endpoint feedback displayed was calculated as if the target were at the larger distance, but was displayed at the shorter distance translated exactly along the direction of the target. (E.g., if the participant reached such that they would have hit the bottom-left side of the target at the farther distance, the endpoint feedback would be displayed in the bottom-left side of the target displayed at the shorter visual distance.). This design maintained the basic procedures of Experiment 3, but ensured that effective goal width was identical within each movement distance condition.

Statistical Analysis

The primary dependent measure was movement duration (MT). Linear mixed-effect models were run using R’s *lmerTest* package. These models were designed to fit MTs during the test phases using fixed effects of both the physical movement extent and the visual distance of the target, with subject ID as a random effect. ANOVA analysis was done using R’s *anova* command on the results of the LMER regression, with automatic sphericity corrections applied. It should be noted that this analysis was only on MTs during the no-feedback test phases, and thus these MTs were not contaminated by corrective movements. We additionally computed the physical error between the movement executed and the ideal movement. This was done by computing the difference between the movement vector that would bring the cursor to the exact center of the target and the vector from the center to where the participant stopped their movement. The error was quantified as the magnitude of this vector. Learning curves were computed using this metric, averaging across trials within each adaptation phase. Lastly, percent error during the adaptation phase indexed the proportion of trials in which participants did not land within the target in the allotted maximum movement time for a given cycle of adaptation trials. All analyses were conducted in R (version 4.2.1).

Modeling

Individual participant MT data were fit using various models all employing the basic Fitts' Law formulation, MT = *a* + *b*log*(2*D*/*W*). The basic predicted patterns of data generated by these models are plotted in **Figure 1d**. The movement-distance-only (MD) model predicts MTs solely using the extent of the participants' hand displacement to set the D term. The visual-distance-only (VD) model predicts MTs solely using the visually displayed distance of the target to set the D term. The multisensory integration (MSI) model employs a weighted average between the movement distance and the visual distance to set the D term on each trial:

$$MT \ = \ a + b * log(\lambda * MD + [1 - \lambda] * VD)$$

where the weighting parameter λ constitutes a third free-parameter in addition to the standard *a* and *b* offset and scaling parameters from Fitts' Law; this additional weighting parameter varied from 0 (only visual distance matters) to 1 (only movement distance matters).

All models assumed the target width was constant, as its visual width was identical across all conditions and experiments. As a control, we also included a fourth model that accounts for differences in "effective goal width" are caused by gain manipulations (see descriptions for Experiment 4a and 4b above for details). This effective width (EW) model performed a weighted average between the visual width (a constant) and the effective width (the inverse of the gain applied on a particular trial):

$$MT = a + b * log\left(\frac{MD}{W_{eff}}\right)$$

$$W_{eff} = \eta / gain \; + \; (1 - \eta)$$

where, if the free parameter η is 1, the width term of Fitts' law is entirely about the effective width of the target, and if η is 0, the width term is completely unaffected by the gain manipulation, reflecting the constant width of the visual target across all conditions.

Model fitting was performed using R's *optim* function, employing the L-BFGS-B optimization method. Model comparison was conducted with the Bayesian information criterion (BIC) computed on the average of model-predicted MTs for each condition and subject. Reported "summed ΔBICs" were computed relative to the mean BIC for each subject across the three main models (MSI, MD, VD). When comparing any two models, mean ΔBICs represent across-subject averages of the difference in BICs for the two models compared. Pseudo-R^2 was computed per subject as $1 - \frac{Model\ SSE}{Null\ SSE}$ where the Model SSE was the sum of squared errors between the model-predicted average MT for each condition and the true average MT for each condition, and the Null SSE was the sum of squared errors between the true average MT for each condition and the average MT for all conditions.

Author's Note

Data and analysis scripts are available at https://zenodo.org/record/8287803. The experiments reported here were not preregistered. Ideas and data presented here were not previously disseminated.

Results

Experiment 1

In this study we aimed to clarify which distance cues determine movement duration in a reaching task. Online feedback was provided and the gain on the cursor was manipulated in order to dissociate the visual distance of the target and the physical movement distance required to hit the target (**Figure 1b**). During the 12-trial adaptation phases, participants largely successfully adapted to the perturbation, achieving reach errors averaging 4.3 mm (95% CI [3.3, 5.3]) from the optimal solution (i.e. the movement need in order for the cursor to land in the center of the target) by the last trial within each adaptation phase. Errors on the last trial were not significantly different between the un-manipulated (gain = 1) and manipulated (gain = 2 or 0.5) conditions (paired t-test, $t(9)=-0.41$, $p=0.67$, $d_z=-0.18$). On average, participants successfully landed within the target on 91.0 % of training trials (95% CI [88%, 94%]; **Figure 2a**). Success rates subtly but significantly differed between conditions (paired t-test, $t(9)=3.59$, $p=0.005$, $d_z=0.72$), with manipulated trials resulting in 5.3% less success on average (88.4% vs 93.7%). While statistically significant, this difference amounts to an average of one additional failed trial per 20 trials.

Movement times during the critical test phase were fit using a linear mixed-effect model. MTs were predicted using fixed effects of true hand displacement and the visual distance of the target, and a random effect of subject ID. True hand displacement was used instead of ideal displacement to better capture the true data, and because participants did not always reach 100% adaptation (**Figure 2b**). Crucially, an ANOVA indicated main effects of both hand displacement ($F(1, 28.35)=36.58$, $p=1.5 \times 10^{-6}$) and the visual distance of the target ($F(1, 28.03)=26.88$, $p=1.7 \times 10^{-5}$) on MTs, suggesting that both factors may influence Fitts' Law (**Figure 2b**).

These results were echoed by our computational modeling (**Figure 2c**): The MSI model (summed ΔBIC=-26) outperformed both the MD (summed ΔBIC =24, mean ΔBIC=-5.00, 7/10 better fit by MSI) and VD models (summed ΔBIC=1.5, mean ΔBIC=-2.72, 6/10 better fit by MSI). The MSI model fit participant trial-type average MTs with a strong pseudo-R^2 of 0.83 (MD:

0.40, VD: 0.54), again supporting the idea that physical distance and visual distance both contributed to MTs.

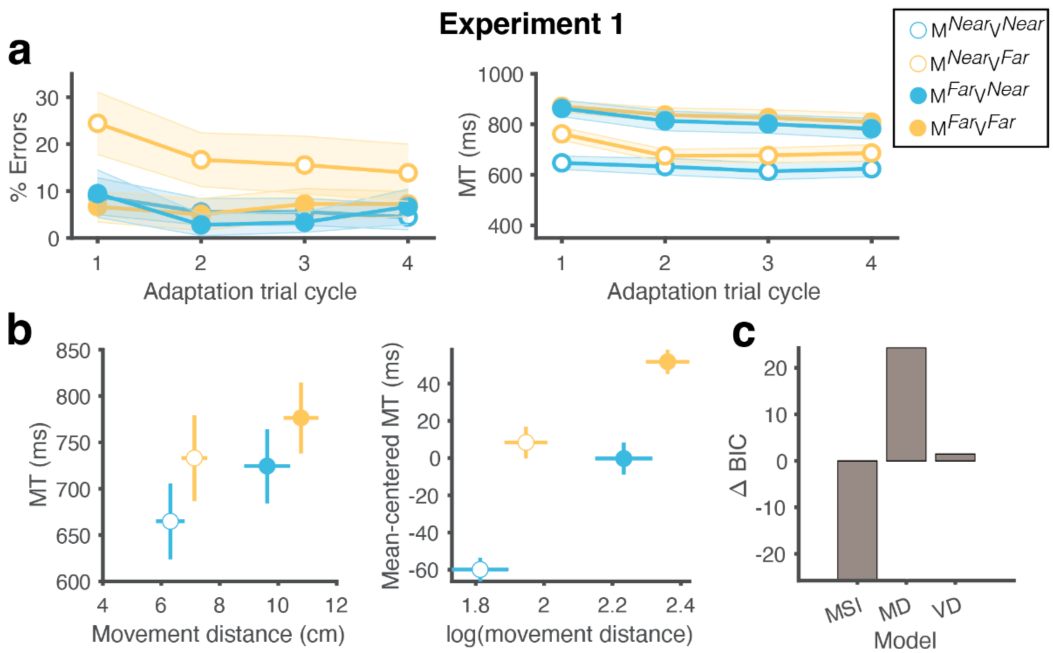

Figure 2. *Experiment 1 results*. **a)** Percent error (*Left*) and MT (*Right*) during the adaptation phase, averaged across mini-blocks for each condition. Adaptation trial cycle reflects the average of 3 reaches, one to each target location. Shaded error bars reflect standard error of the mean (SEM). Percent error reflects binary target-hitting success by the maximum movement time, averaged across mini-blocks for each cycle. **b)** Test phase MTs (*Left:* raw, *Right:* mean-centered) plotted against the distance moved by the participant (*Left:* raw, *Right:* log-scaled), averaged for each of the four conditions. Error bars reflect SEM for both the movement distance data (horizontal error bars) and MT data (vertical error bars). **C)** Summed ΔBIC for the three main models (MSI: Multi-Sensory Integration; MD: Movement Distance; VD: Visual Distance), computed relative to the average BIC for all three models in order to visualize differences. Lower values translate to stronger model fits.

As an additional control, participant MTs were fit using the EW model, which controls for the gain perturbation's tendency to modify error tolerances (see *Methods*). Critically, this model failed to beat the MSI model (mean ΔBIC=4.65, 8/10 better fit by MSI). Lastly, the key free parameter in the MSI model (λ), which lineary averages the visual and movement distances, had a mean value of 0.53 (95% CI [0.28, 0.78]), indicating that roughly 53% of the D term in Fitts' Law was reflective of the movement distance and 47% was reflective of the perceived visual distance of the target. Having demonstrated effects of both movement and visual distance on MT, we next asked if we could alter the relative weighting of both variables.

Experiment 2

Experiment 2 was identical to Experiment 1 but was conducted online. The online format was chosen so that actions would be restricted to small mouse movements, significantly decreasing the difference between the physical movements required by each condition but maintaining large visual differences. It was hypothesized that this restriction would reduce the effect of the hand displacement on the index of difficulty (ID), and thus emphasize the effect of the visual distance of the target.

During the 12-trial adaptation phases, participants adapted to gain perturbations when they were present: By the last trial of the adaptation phase, errors from the optimal movement averaged 15 pixels (25% of the target diameter; 95% CI [13, 16] px). Since Exp. 2 was conducted online, these errors reflect the error of the mouse displacement in the absence of any gain manipulation from the mouse displacement that would have been necessary to hit the center of the target. (These errors cannot be cleanly translated into physical distances since computer mice and trackpads do not report their sensitivities for security reasons, but it should be noted that 15px is roughly 4mm on a screen.) Unlike in Experiment 1, errors differed subtly between manipulated and un-manipulated trials: Errors on the last training trial within a block were significantly larger when the cursor gain was manipulated (paired t-test, $t(26)=-4.3$,

$p=2.4\times10^{-4}$, $d_z=-0.92$) by an average of 4.4px (95% CI [2.3, 6.6] px). This also corresponded to differences in success rates (**Figure 3a**): Across all training trials, manipulated trials had significantly lower success rates (paired t-test, $t(26)=2.69$, $p=0.01$, $d_z=0.54$) by an average of 2.1% (95% CI [0.5%, 3.6%]). Nonetheless, participants averaged 96.8% (95% CI [95.5%, 98.0]) success across all adaptation trials, indicating a high degree of success and rather small accuracy differences between conditions.

Test phase MTs were once again well predicted by both movement distance and visual distance, but primarily the latter (**Figure 3b**). An ANOVA analysis over the linear mixed-effect regression on MTs showed a significant main effect of both movement ($F(1, 86.38)=4.35$, $p=0.04$) and visual distance ($F(1, 79.25)=30.9$, $p=3.5\times10^{-7}$). As hypothesized, the role of movement distance was substantially diminished relative to the veridical context of Exp. 1, likely due to the fact that in Exp. 2 the required kinematic displacements were dwarfed by their corresponding visual displacements. Instead, MTs were largely modulated by the visual distance of the target (**Figure 3b**).

This result was further supported by modeling (**Figure 3c**): while the MSI model (summed ΔBIC=-17) beat the MD model (summed ΔBIC=50, mean ΔBIC=-2.51, 15/27 better fit by MSI), it did not beat the VD model (summed ΔBIC=-33, mean ΔBIC=0.59, 9/27 better fit by MSI). We note that the VD model performs well here because it has fewer parameters than the MSI model, and the data indicates almost a near-complete dominance of visual distance, as hypothesized. The MSI model fit participants' trial-type MTs with a pseudo-R^2 of 0.53 (MD: 0.19, VD: 0.46). As a further control, the EW model, which controls for task geometry-induced differences in difficulty, did not win by BIC (mean ΔBIC=-0.85, 13/27 better fit by MSI, pseudo-R^2=0.53). Having shown that we can downweight the role of movement distance and upweight the role of visual distance in Fitts' Law, we next tried to do the opposite.

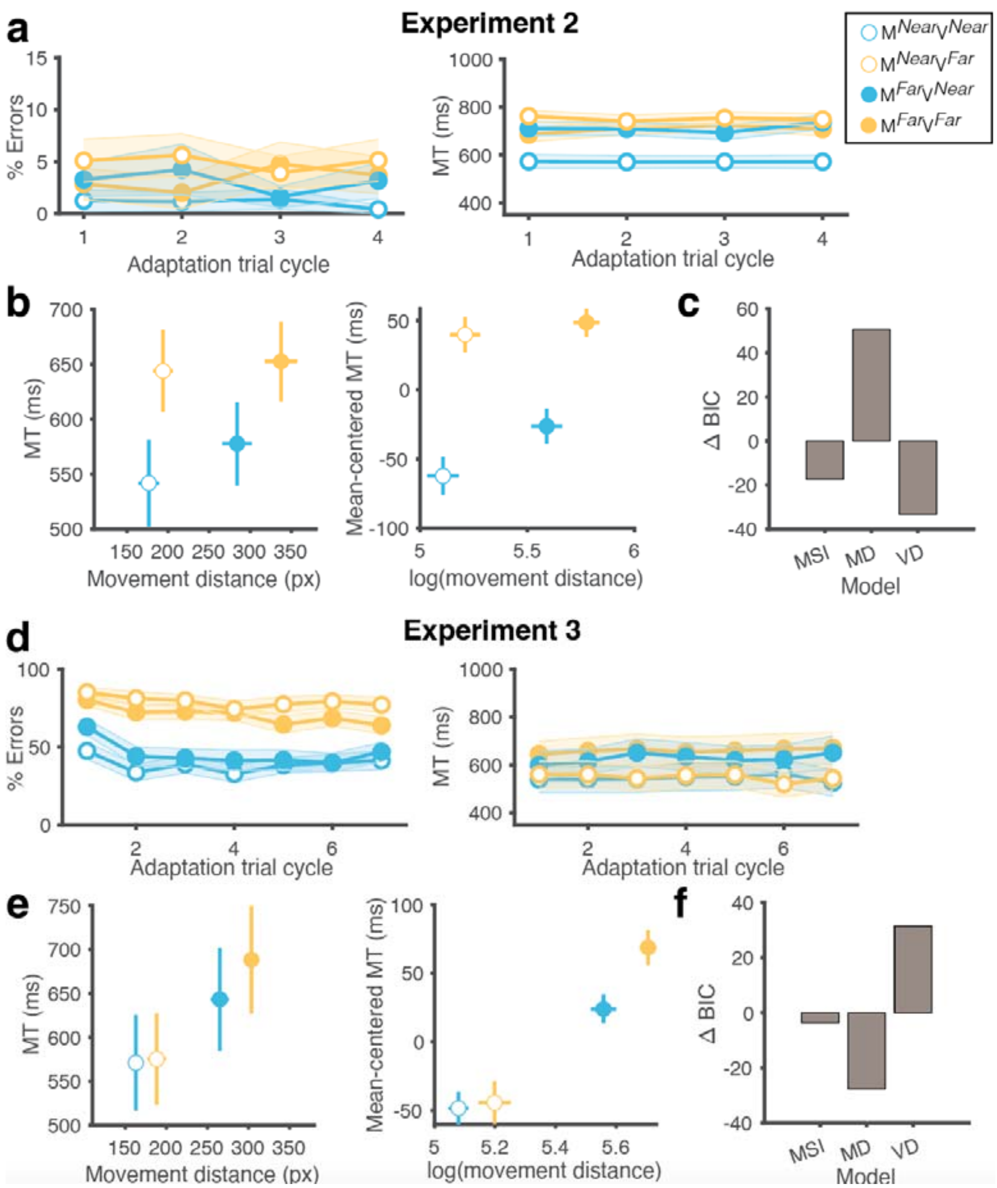

Figure 3. *Experiment 2 and Experiment 3 results*. **a, d)** Percent error (*Left*) and MT (*Right*) during the adaptation phase averaged across mini-blocks for each condition for Exps. 2 and 3, respectively. Shaded error bars reflect standard error of the mean (SEM). **b, e)** Test phase MTs (*Left:* raw, *Right:* mean-centered) plotted against the distance moved by the participant (*Left:* raw, *Right:* log-scaled), averaged across all four conditions for Exps. 2 and 3, respectively. Error bars reflect SEM for both the movement distance data (horizontal error bars) and MT data (vertical error bars). **c, f)** Summed ΔBIC for the three main models (MSI,

MD, VD) for Exps. 2 and 3, respectively. Lower values translate to stronger model fits.

Experiment 3

The results of Experiments 1 and 2 suggest that both movement and visual distances can influence Fitts' Law, and that the role of visual distance can be amplified by restricting the range of movement distances relative to visual distances. In Experiment 3, we asked if the opposite effect could be elicited, such that movement distance alone could be made to shape MTs even under the restricted movement range conditions of Exp. 2. Thus, in Experiment 3 we provided only endpoint feedback during the adaptation phase. This degraded visual feedback should, we reasoned, lessen the salience of the visual aspects of the task and increase the salience of the kinesthetic aspects, and consequently boost the effect of movement distance on MTs while attenuating the effect of visual distance.

Due to the degraded feedback, participant errors were predictably larger in Exp. 3 compared to Exp. 2. Movement errors on the last trial of the adaptation phase were on average 67.6px (89% of the diameter of the target or roughly 1.8cm on the screen, 95% CI [54, 81] px). Errors were predictably larger for conditions where the required movement distance was longer (paired t-test, $t(26)=2.83$, $p=0.009$, $d=0.54$) by an average of 44px (95% CI [12, 76])]. Additionally, errors on perturbation trials were significantly larger compared to un-manipulated trials (paired t-test, $t(26)=-2.51$, $p=0.02$, $d=-0.38$) by an average of 14.7px (95% CI [3, 27] px). Success rates (**Figure 3d**) were higher for shorter visual distance trials (paired t-test, $t(26)=17.1$, $p=1.2\times10^{-15}$, $d=1.65$), by an average of 32.6% (95% CI [29%, 37%]). Manipulated trials also had lower success rates (paired t-test, $t(26)=4.72$, $p=7.0\times10^{-5}$, $d=0.46$), by an average of 7.7% (95% CI [4%, 11%]). Overall, success rates were vastly lower in Exp. 3 (as was expected, given the lack of online feedback), with average success across all training trials at 41.4% (95% CI [35%, 48%]) despite the lengthened adaptation phase (21 trials).

Participant MTs were well predicted by movement extent, but, critically, not by visual distance (**Figure 3e**): An ANOVA analysis revealed a main effect of movement distance on MTs ($F(1, 79.66)=42.58$, $p=5.8\times10^{-9}$) but no significant effect of visual distance ($F(1, 79.04)=0.03$, $p=0.87$). Model comparison (**Figure 3f**) using BIC indicated that the MD model (summed ΔBIC=-28) was the best-fitting model (compared to MSI [summed ΔBIC=-3]: mean ΔBIC=-0.88, 24/27 better fit by MD; compared to VD [summed ΔBIC=31]: mean ΔBIC=-2.18, 20/27 better fit by MD). However, the MSI model had the highest pseudo R^2 at 0.46 (MD: 0.41, VD: 0.12). The control EW model was largely equivalent to the MSI model (mean ΔBIC=-0.16 in favor of EW, 13/27 better fit by EW).

These observations support the conclusion that MTs in Exp. 3 were primarily determined by movement distances as opposed to visual distances, in stark contrast to Exp. 2. Given that the underlying gain manipulation in Exp. 3 was identical to Exps. 1 and 2 and that the movement demands fully matched Exp. 2, the complete flip in the factor shaping MTs from visual to movement distance appeared to be driven solely by the change in visual feedback. Taken as a whole, the results of Exps. 1-3 point to both movement and visual distance independently influencing the D term in Fitts' Law.

Experiment 4a

Experiments 1-3 employed conventional gain perturbations in which small displacements, Δx, are displayed as $\Delta x * gain$. As a result of this, the "effective width" (that is, differences in error tolerance in gain versus non-gain contexts; see *Methods*) of the movement targets varies across conditions with different gains, in that gain can inflate or deflate errors in initial movement direction and extent. (For example, when gain = 2, any slight deviation from the correct movement amplitude would be magnified two-fold in the observed visual error.) To control for this geometric difference, which is inherent to gain perturbations, Experiments 4a and 4b employed a novel translational perturbation where the visual feedback was "teleported" along the straight-line path to the target to either a greater or shorter amplitude, depending on the gain. The size of the effective area of successful reach vectors was thus standardized for all conditions.

Due to the discrete nature of this perturbation, only endpoint feedback could be provided. Despite this degraded feedback, participants learned to adequately adapt to the perturbation during gain trials, achieving average errors of 13.3mm (67% of target diameter; 95% CI [11, 16] px) on the last trial of the adaptation phase. Errors were significantly larger for the larger movement distance trials (paired t-test, $t(9)=-6.10$, $p=1.8\times10^{-4}$, $d=-1.82$) by an average of 7.9 mm (95% CI [5, 11] mm). However, errors were not significantly different between manipulated and un-manipulated trials (paired t-test, $t(9)=-0.86$, $p=0.41$, $d=-0.33$). Consistent with the larger errors, conditions with greater movement distances also had lower success rates (**Figure 4a**; paired t-test, $t(9)=9.43$, $p=5.8\times10^{-6}$, $d=2.11$), by an average of 27% (95% CI [21%, 34%]), broadly consistent with Fitts' Law. Notably, the pattern of difficulty differences between conditions in Exp. 4a, as reflected in success rates (**Figure 4a**), deviated from the pattern seen in Exp. 3 (**Figure 3d**), signaling the success of our novel "difficulty clamp" perturbation method.

Even with a rather different perturbation applied, the test phase results of Experiment 4a largely replicated the results of Experiment 3 (**Figure 4b**). Specifically, the ANOVA analysis revealed a main effect of movement distance ($F(1, 28.04) = 144.4$, $p=1.4\times10^{-12}$) but not visual distance ($F(1, 28.00) = 0.06$, $p=0.81$) on MT. Modeling further corroborated these results (**Figure 4c**): By BIC comparison, the MSI (summed ΔBIC=31) and MD (summed ΔBIC=32) models were largely identical in fit quality (mean ΔBIC=-0.08 in favor of MD, 6/10 better fit by MD). However, the MSI model had a pseudo-R^2 of 0.89, as opposed to the MD model at 0.79. The average value of the fitted λ parameter was 0.91 (SD: 0.11), indicating that movement distance contributed ~91% of the *D* term in Fitts' Law. Thus, even after accounting for the effect of varying effective target widths and altering the pattern of adaptation phase errors across conditions relative to Exp. 3, the key results of Exp. 3 were replicated in Exp. 4a.

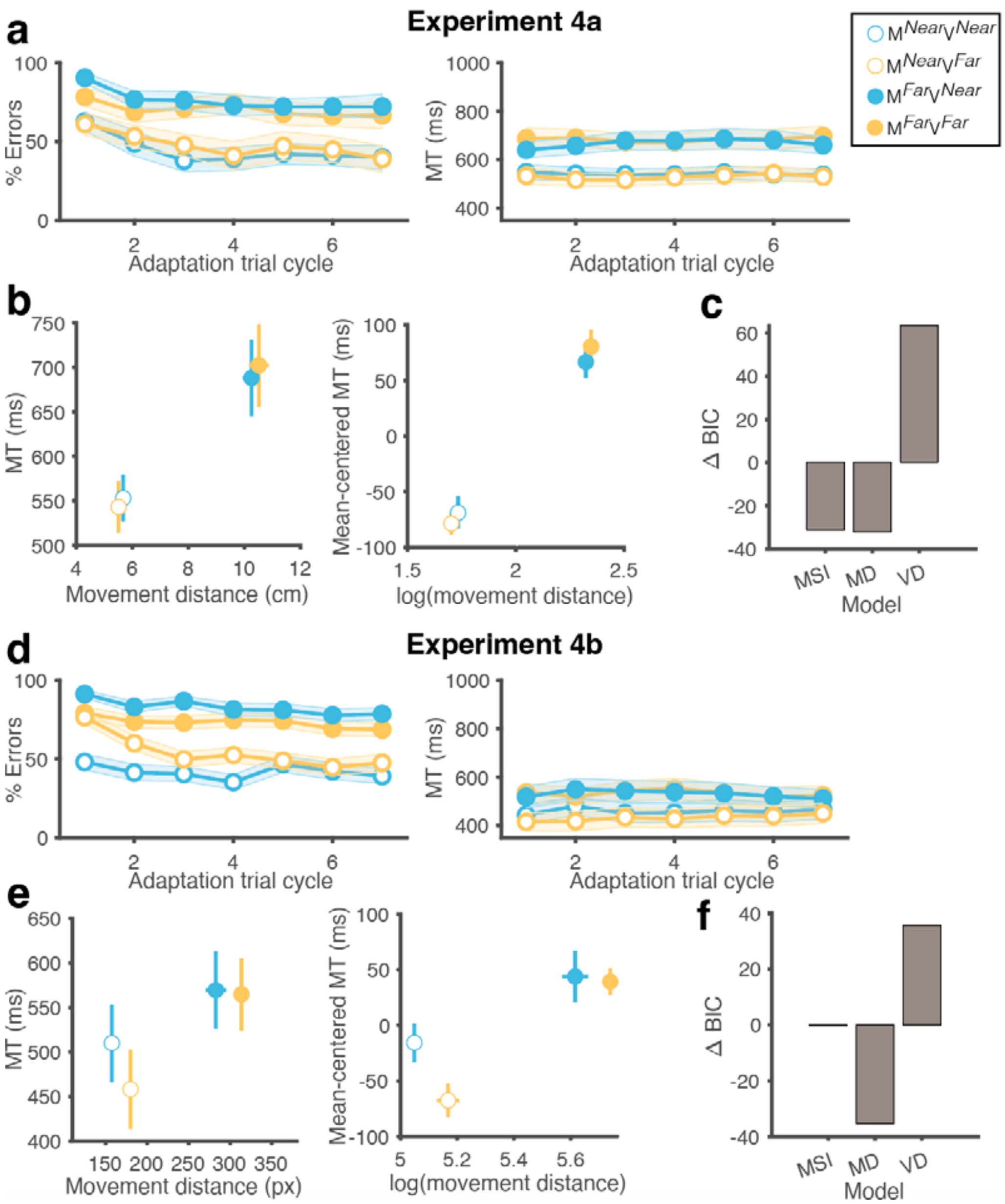

Figure 4. *Experiment 4 results*. **a, d)** Percent error (*Left*) and MT (*Right*) during the adaptation phase averaged across mini-blocks for each condition for Exps. 4a and 4b, respectively. Shaded error bars reflect standard error of the mean (SEM). **b, e)** Test phase MTs (*Left:* raw, *Right:* mean-centered) plotted against

the distance moved by the participant (*Left:* raw, *Right:* log-scaled) averaged across all four conditions for Exps. 4a and 4b, respectively. Error bars reflect SEM for both the movement distance data (horizontal error bars) and MT data (vertical error bars). **c, f)** Summed ΔBIC for the three main models (MSI, MD, VD) for Exps. 4a and 4b, respectively. Lower values translate to stronger model fits.

Experiment 4b

Here, we replicated Exp. 4a in an online sample. As with Exp. 3, the degraded visual feedback led to relatively large errors on the last trial of the adaptation phase, averaging 67.7px (1.8cm or 89% of the diameter of the target; 95% CI [58, 78] p). Errors were significantly larger on trials where the movement amplitude was greater (paired t-test, $t(29)=-5.10$, $p=1.9\times10^{-5}$) by an average of 35.3px (95% CI [21, 49] px). Errors were marginally different between manipulated and un-manipulated trials (paired t-test, $t(29)=-2.00$, $p=0.054$, $d=-0.33$), with errors 10.5px (~2.8mm; 95% CI [0, 21] px) larger for manipulated trials. Shorter movements had significantly higher success rates (**Figure 4d**) throughout training (paired t-test, $t(29)=21.2$, $p=2.2\times10^{-16}$, $d=2.26$), by an average of 30% (95% CI [27%, 33%]); un-manipulated trials also had significantly higher success rates (paired t-test, $t(29)=9.32$, $p=3.2\times10^{10}$, $d=0.96$), by an average of 11% (95% CI [9%, 13%]).

Test phase movement durations in Exp. 4b were again only weakly predicted by visual distance, consistent with degraded feedback downweighting vision's role (**Figure 4e**): The ANOVA revealed a main effect of movement distance, as expected ($F(1, 90.19)=22.86$, $p=6.7\times10^{-6}$), and, a small but significant main effect of visual distance ($F(1, 87.98)=5.30$, $p=0.02$). However, the longer visual distances actually predicted lower MTs, an effect that was largely driven by faster MTs on the condition where the movement goal was near but the visual target was far. Interestingly, for this condition, when compared to the un-manipulated near-movement condition, participants had marginally larger errors ($t(29)=1.77$, $p=0.09$, $d=0.38$;

13.8px, 95% CI [-2, 30] px) and significantly lower success rates ($t(29)=6.76$, $p=2.04\times10^{-7}$, $d=0.86$; 12%, 95% CI [9%, 16%]) during adaptation phases, yet had faster MTs during the test phase ($t(29)=-2.40$, $p=0.02$, $d=-0.22$; 52ms, 95% CI [8, 96] ms).

Modeling supported the conclusion that MTs were predominantly driven by movement distance (**Figure 4f**): The MD model (summed ΔBIC=-35) won model comparison by BIC, beating the MSI model (summed ΔBIC=0, mean ΔBIC=-1.17, 27/30 better fit by MD) and the VD model (summed ΔBIC=36, mean ΔBIC=-2.37, 22/30 better fit by MD). The MSI model had a slightly higher pseudo-R^2 compared to the MD model (MSI: 0.38, MD: 0.36, VD: 0.05). We note that the lower pseudo-R^2 values in general arise from the models' inability to account for the aforementioned violation of Fitts' Law in one of the conditions.

Overall, the key test phase findings of both Exps. 4a and 4b did not differ from the results of Experiment 3 – this echoes the poor fit of the EW model in the previous studies, and further suggests that the key results of our study were likely not driven by differences in target effective widths or other difficulty considerations. Instead, the four experiments suggest that both movement distance and visual distance can influence Fitts' Law.

Discussion

What information does the brain use to predict the difficulty of a movement? Across four experiments we sought to clarify the nature of the movement distance (D) term of Fitts' Law (**Figure 1d**). We leveraged gain adaptation (**Figure 1b**) to create conditions where both visual and kinesthetic aspects of a reaching task could independently influence movement times (MTs). Our results showed that when continuous visual feedback is provided during adaptation (Exps. 1 & 2), the visually perceived distance of a goal and the reach amplitude needed to reach that goal both contributed to MT (**Figures 2 and 3**). The role of vision was especially pronounced when movement amplitudes were restricted relative to visual distances (Exp. 2; **Figure 3**). However, when visual feedback was degraded to only appear at the endpoint of a movement, visual goal distance no longer predicted MT even within the same restricted movement context (Exp. 3; **Figure 3**). When potential condition difficulty differences due to the geometry of the task were accounted for (Exp. 4a & b; **Figure 4**), these latter results remained largely unchanged. Crucially, all of our key results were quantified in a test phase where visual feedback was withheld. Thus, differences in MTs could not be explained by online, corrective movements or similar reactive strategies.

What is the underlying process that explains our findings? We speculate that visual distance may exert an effect during an early motor planning stage (Al Borno et al., 2020). The visual distance to the goal, even when decoupled from the required movement distance, may act as a "prior" on the expected difficulty of a movement. The results of Exps. 1-2 demonstrate that visual distance independently affects MT, and Exps. 3 and 4 show that the removal of continuous visual feedback during adaptation decreased the influence of visual distance; this is likely because subjects had to rely heavily on proprioception in these conditions. The distinct behavioral effects of online versus endpoint feedback we observed are consistent with findings in motor adaptation that show similar tradeoffs between vision and proprioception in online versus endpoint feedback conditions (Hayashi et al., 2020; Izawa & Shadmehr, 2011). Taken together, our results may reflect an integration of visual and proprioceptive information in the computation of the D term in Fitts' Law.

Another consideration here is the role of attention: It may be that continuous visual feedback (Exps. 1-2) biased people's attention to visual cues during online control of the cursor; in contrast, endpoint feedback (Exps. 3-4) may have biased attention to proprioceptive cues (the felt distance of the hand) to facilitate estimation of the correct reach stopping point. Put another way, putative multisensory integration in our task may occur at the level of conscious attention to vision versus proprioception. This attentional account could help explain our results and is an interesting theoretical direction. However, the attentional account is somewhat undermined by the fact that all of our key results were observed in a testing phase where feedback was removed and was thus identical between conditions. It is worth considering that our gain perturbation may be compensated for by a combination of explicit and implicit motor learning processes (Krakauer et al., 2004; McDougle et al., 2016; Taylor et al., 2014). Future work could target the role of explicit cognitive processes versus implicit motor planning processes in our task, and in Fitts' Law more generally.

It is unlikely that test phase MTs were significantly impacted by the latent changes in task geometry due to gain perturbations: When we directly controlled for these intrinsic condition difficulty differences in Exp. 4, the results of Exp. 3 largely replicated. Furthermore, the integrative MSI model was able to explain MT results across multiple experiments and only failed when it was overfit because a single factor explained the data. While this does not fully rule out a potential role of the 'effective width' (see *Methods*) of reach targets in our task, in Exps. 1-3, vastly different visual and movement distance effects were observed even when effective widths did not differ across the experiments.

In general, when performance during adaptation was relatively weak, test phase MTs were slower. This was predictable (Adam, 1992; de Grosbois et al., 2015; Fitts, 1954; Fitts &

Peterson, 1964; van Donkelaar, 1999) – Fitts' Law relates the difficulty of a movement to its duration. However, we did not always see a 1-1 relationship between success during the adaptation phase and the key MT results in the testing phase (**Figure 4**). While it is difficult to fully separate effects of accuracy and movement time (their close relationship is the point of Fitts' Law), one limitation of our study is that it targeted MT effects following gain adaptation which may account for additional difficulty variables not accounted for in our models. In Experiments 1 and 2, participants may have learned to associate particular visual distances with the ease of cursor control and the cursor speed. However, these associations persisted into the probe phase where no feedback was provided, suggesting still that visual cues of difficulty (namely visual target distance) were integrated into movement durations under Fitts' Law. This is parsimoniously explained by our model of the D term of Fitts' Law. Future studies could further explore these additional aspects of difficulty.

More broadly, we think our results could contribute to a synthesis of documented amendments to Fitts' Law (Crossman & Goodeve, 1983; de Grosbois et al., 2015; Heath et al., 2011). First, our findings are consistent with literature suggesting that strategic attention to a range of task dimensions shape Fitts' Law (Adam, 1992). Our results also echo and extend findings that Fitts' Law can emerge at perceptual or mental "simulation" stages of motor planning (Decety & Jeannerod, 1995; Grosjean et al., 2007), are consistent with findings that visual illusions can bias Fitts' Law (van Donkelaar, 1999), and comport with studies relating the law to more abstract features of motor preparation and planning (Augustyn & Rosenbaum, 2005; Jax et al., 2007). Incentives also modulate movement durations (Ashworth-Beaumont & Nowicky, 2013; Bogacz et al., 2010; Du et al., 2022; Listman et al., 2021; Thura et al., 2014), further supporting flexibility in the strategies the brain employs when selecting movement parameters. Future investigations can address other non-motor indicators of difficulty, such as the visually inferred weight of a tool (Ellis & Lederman, 1993).

As interest in the applicability of Fitts' Law to virtual and augmented reality grows (Rohs et al., 2011; Rohs & Oulasvirta, 2008; Sambrooks & Wilkinson, 2013), it is important to understand the law's underlying mechanisms. We demonstrated here that under certain conditions, fundamental variables in Fitts' Law are responsive both to perceptual (visual goal distance) and physical (movement distance) cues. Developers of AR/VR applications could leverage this observation in optimizing or calibrating the feedback they provide to users. Our results may also inform investigations into the neural correlates of action selection and the speed-accuracy trade-off (Al Borno et al., 2020; Harris & Wolpert, 1998) perhaps serving to illuminate distinct factors that the motor system represents as it prepares fast and accurate actions.

Constraints on Generality

Fitt's Law is a surprisingly robust psychophysical law with broad applicability. Samples reported here may not be generally representative of the global population as participants were recruited from the US. Nonetheless, we believe these results should broadly apply to all neurotypical adults, as they relate to the typical performance of goal-directed movements.

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