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MOTOR PSYCHOPHYSICS:

DEVELOPING A METHOD FOR MEASURING MOVEMENT-RELATED EFFORT

A Thesis in

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Chason J. Coelho

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The thesis of Chason J. Coelho was reviewed and approved* by the following:

D. A. Rosenbaum
Distinguished Professor of Psychology
Thesis Adviser

Nancy Dennis
Assistant Professor of Psychology

W. J. Ray
Professor of Psychology

Robert Sainburg
Professor of Kinesiology and Neurology

Melvin M. Mark
Professor of Psychology
Head of the Department of Psychology

* Signatures are on file in the Graduate School

ABSTRACT

Motor planning theories suggest that the movements people perform are generally less effortful than the alternatives that could complete the task at hand. However, there is no established method for estimating movement-related effort. I used a task-choice method to address this challenge. On each trial, I presented participants with two paced back-and-forth object displacement tasks that varied along well defined dimensions. I asked participants to perform whichever task seemed easier. Based on the assumption that effortful tasks were less popular, I took the pooled likelihood that certain tasks were chosen as an estimate of how much effort participants ascribed to the task dimensions. I manipulated movement distance, required speed, dominant vs. non-dominant hand use, body leaning, and momentum. I fitted the choice data with a mathematical that ascribed significant degrees of effort to required speed, non-preferred hand use, and body leaning. The model also made claims about how participants integrated and compared these multi-modal costs. This work demonstrates the promise of the task-choice method for estimating movement costs in reaching tasks and helps establish a rigorous approach to the study of movement-related effort.

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Chapter 1

INTRODUCTION

When you reach for a cup of coffee, open a door, or press an elevator button, you probably pay little attention to which hand you use or how quickly you move it. Although everyday reaching tasks are performed with ease, at least in neurologically normal adults, older children, and their animal analogs, it remains unclear which strategies people (and animals) adopt for performing them. Motor planning theories suggest that when people decide how to move, they implicitly consider the costs, or degrees of effort, of potential actions (Erlhagen & Schöner, 2002; Rosenbaum, Meulenbroek, Vaughan, & Jansen, 2001; Sparrow & Newell, 1998; Todorov, 2004). These theories assume that performed physical actions entail less effort than unperformed but possible physical actions. A method for independently estimating effort is needed to validate this assumption. Here I discuss how previous methods used for reaching tasks may be limited. Then I describe a task-choice method that addresses those limitations. I next present data from an experiment that used the method. I conclude by discussing the implications of the results for research in this field of study.

Several researchers have used energy expenditure as an index of effort (see Srinivasan, 2009, for review). For example, Hoyt and Taylor (1984) measured horses' oxygen consumption levels during locomotion and showed that gait transitions occurred at energetically optimal times. Although this measure of effort is viable for gross actions like walking and running, it probably is not sensitive enough to be used in finer motor tasks. It seems unlikely that oxygen consumption levels would vary appreciably across reaches of somewhat different lengths, for example.

Other research has focused more specifically on the biomechanical energy expended in moving some mass over a certain distance (Gengerelli, 1930; Hull, 1943; Tsai, 1932; Waters, 1937). In an early study, Gengerelli (1930) placed rats in the corner of a box and food in the opposite corner. The question was simple: Of all the paths the rats could take to the food, which path would they choose? Perhaps unsurprisingly, the rats preferred straight paths. This result led Gengerelli to conclude that the rats chose actions that afforded biomechanical efficiency. It is clear, nonetheless, that other parameters, such as speed and time, influence how much energy is expended during movement (Waters, 1937; Winter, 1990). This observation raises the possibility that multiple costs contribute to perceived effort.

Recent research in humans has provided additional support for the idea that effort is a multimodal construct that combines different costs (e.g., Dickerson et al., 2007; Kahneman, 1973; Rosenbaum & Gregory, 2002). Rosenbaum and Gregory (2002; Experiment 1) had participants assign effort ratings to movements, a method first introduced by Borg (1973). Participants oscillated a cursor at different frequencies between two targets on a screen. Rosenbaum and Gregory varied how far the cursor moved relative to the hand. They hypothesized that larger hand displacements would yield higher effort ratings. Contrary to this prediction, participants rated small movements that produced large jumps in the cursor as more effortful than large movements that produced small cursor jumps. Although there is no a priori reason to conclude that this outcome is “wrong,” it suggests that effort ratings reflected the difficulty of achieving precision rather than the effort of moving per se. When participants in a second experiment were asked to produce hand displacements in a way that matched different prescribed levels of effort, they increased the displacement of their hands as both instructed effort and driving frequency increased. Taken together, these findings suggest that movement-related effort is linked to both precision requirements and movement speed.

Dickerson et al. (2007) used a similar reaching task and found that effort ratings positively correlated with shoulder muscle forces. However, these authors cautioned that “effort is a complex quantity that may integrate components beyond those described by an image of the motor command” (p.1014). This body of work indicates that movement-related effort entails many costs. It also suggests that the method of asking participants to make post-hoc effort ratings of an action may be insensitive to how multi-modal costs contribute to perceived effort.

It would be helpful to have a method that can be used both to estimate the costs of different factors and help reveal how those multi-modal costs are integrated. A useful approach to this challenge is to appeal to psychophysics, a field concerned with describing how physical quantities are psychologically represented. An example of a psychophysical problem is determining how frequencies of sound waves are perceived in terms of pitch. While sound wave frequencies can be measured with electronic instruments, the estimation of pitch magnitudes can only be determined through a human observer's response to sound (Stevens & Davis, 1963). Thus, psychophysical procedures often require participants to decide whether pitches of different tones are larger or smaller than the pitch of a reference tone (for review, see Gescheider, 1997). The relations between frequencies and judgments are used to estimate the relations between frequency and pitch. A convenient feature of this approach is that judgments need not be restricted to stimuli of the same sensory modality. Rather, one can compare cross-modal magnitudes, for example, by asking participants whether the intensity of a reference tone is larger or smaller than the intensity of a visual or haptic stimulus (Stevens, 1957).

Similar methods can be used to estimate effort in reaching tasks. For example, Rosenbaum and Gaydos (2008) used a task-choice procedure to estimate the perceived cost of physical task factors. On each trial, these investigators presented participants with two possible tasks and asked them to perform whichever seemed easier. The tasks varied along well-defined dimensions, and the judged relative cost (JRC) of each task (its relative effort) was quantified as 1 minus the pooled probability that it was chosen. The JRCs of all the tasks were compared to reveal the physical determinants of effort.

Because the overarching goal of the present study is to develop the task-choice method, it is worth saying a little more about the experimental design Rosenbaum and Gaydos (2008) used. Participants stood before 15 possible target positions arrayed on the surface of a table. The targets occupied three distances and five radial directions from a home position located directly in front of the standing participant. On each trial, each participant was asked to use his or her right hand to move a standing toilet plunger (a convenient manipulandum) from the home position to the easier of two given target locations. Each participant made a decision between every possible pair of targets.

Using the analysis described above, Rosenbaum and Gaydos (2008) showed that movement distance predicted JRCs for object displacements. Participants reliably chose to cover shorter distances over longer distances, consistent with the notion that longer distances were more costly than shorter distances. Movement direction had a minimal effect.

These results are not especially surprising, as acknowledged by Rosenbaum and Gaydos (2008), but also as indicated by these authors, the results show that the task-choice method can be used to quantify task effort. Rosenbaum and Gaydos (2008) suggested that future research could capitalize on the simplicity and flexibility of the method to estimate the costs of other task dimensions.

Following this suggestion, in the present study I used the task-choice method to assess the cost of movement distance with respect to time (movement speed), momentum (velocity times mass), body leaning, and hand choice. I also developed a statistical model that revealed how much variance in the effort estimates could be explained by each factor. Next I explain why I investigated the factors that I did.

Rosenbaum and Gaydos (2008) found that longer movement distances were judged more costly than shorter ones. However, they did not control or manipulate movement times, making it unclear whether participants were sensitive to movement distances per se or to movement speeds (mathematically unsigned distances divided by times). Because people can voluntarily control the rates of their movements when task demands call for higher or lower speeds, actors seem sensitive to the costs associated with movement speed and can plan their movements accordingly.

The importance of estimating speed-based movement costs is further highlighted by the fact that models of human movement commonly focus on speed or velocity. For example, a model developed by

Zhang, Kuo, and Chaffin (1998) claimed that movement choices rely on velocity-based optimization. According to this model, the motor system determines the dynamic postures of reaching movements by controlling the rate of hand displacements. Similar models have been used to predict limb trajectories in two-dimensional space (Kaminski & Gentile, 1986, 1989; Morasso, 1981). The success of these models depends on their inclusion of velocity, suggesting that velocity, or some factor closely related to velocity, is an important planning variable.

If people are sensitive to the velocity of object displacements, they may also be sensitive to momentum (velocity times mass) because changes in momentum are proportional to the force required to move the mass. Support for the idea that momentum can influence perceived movement costs comes from studies showing that the weight of handheld objects affects effort ratings in manual lifting tasks (Dickerson et al., 2007; Yeung, Genaidy, & Deddens, 2002).

The third factor I assessed was leaning. In the Rosenbaum and Gaydos study, tasks that required participants to cover long distances also required participants to lean more because those targets were farther away. Perhaps far distances were more costly because they required more leaning. My assessment of leaning costs respects the fact that people must control upper-body posture to maintain balance. The more people lean over, the more their balance is jeopardized (Riley, Mann, & Hodge, 1990).

The final factor I considered was hand choice. Participants in the Rosenbaum and Gaydos study never had to choose between moving the object with the left hand or right. Because a growing body of research suggests that reaching costs may differ for the dominant and non-dominant hands (Carey, Hargreaves, & Goodale, 1996; Carson, 1993; Elliott et al., 1993; Flowers, 1975; Healy, Liederman, & Geschwind, 1986; Helbig & Gabbard, 2004; Mamolo et al., 2004; Peters, 1995; Sainburg, 2002; Sainburg & Kalakanis, 2000), it remains important to clarify how people negotiate limb performance asymmetries during planning.

To estimate the costs of these factors, I used a variation of the task-choice method. On each trial, I asked participants to perform what they perceived to be the easier of two possible tasks. For the sake of analysis, I called one of these the constant task and the other the alternative task. While both tasks required a series of back-and-forth movements in time with a metronome, the movement distance did not vary in the constant task. This feature of the design was meant to simplify the method. Whereas Rosenbaum and Gaydos (2008) compared the pooled probability that participants moved to each target with the probability that participants moved to each of its alternatives, I focused on the pooled probability that participants performed the constant task.

Chapter 2

METHOD

To provide context for the detailed description of the methods that follow, I want to first describe the general features of the experimental setup used here. An overhead schematic of the apparatus is shown in Figure 1. Participants stood at the edge of a table and performed all movements from a standing position. A pair of endpoint targets defined the movement distance in each task. At the beginning of each trial, the to-be-moved object for each task stood on the nearest target of the target pairs for that trial. One task corresponded to each hand. If participants chose the task on the left, they had to move the left object back and forth between the designated targets with the left hand. If they choose the task on the right, they had to move the right object back and forth with the right hand. As noted above, the dependent variable was the overall probability, pooled across participants, that the constant task was chosen.

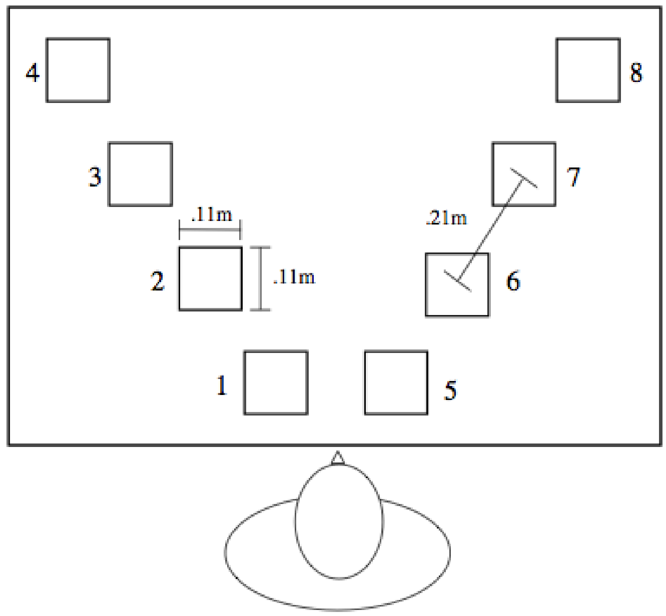

Figure 1. Schematic overhead view of the experimental setup. Participants stood in front of a table and moved a toilet plunger back and forth between two targets on the left or back and forth between two targets on the right.

Participants

One hundred and sixty right-handed undergraduate students—99 women and 61 men—with a mean height of 170.35 cm (*SD* =10.22 cm) and a mean weight of 65.96 kg (*SD* = 12.30 kg) participated in exchange for course credit. Participants reported using their right hand to perform at least 7 out of the 11 tasks listed on the Edinburgh Handedness Inventory (Oldfield, 1971). The mean number of tasks participants said they perform with their right hand was 10.35 (*SD* = 1.39). None of the participants had previously performed object-displacement tasks in this laboratory. All participants read and signed a consent form approved by the Penn State University Institutional Review Board.

Materials

The apparatus occupied the surface of a .76 m high x 1.51 m wide x .76 m deep table. There were two radial arms with possible target locations located at 45° and 135° relative to the near horizontal edge of the table. Each arm had four targets made of blue paper squares (.11 m X .11 m). The centers of the targets in each radial arm were .21 m away from each other. The middles of the targets nearest the participant in each radial arm were both approximately .21 m away from the participant's midline and were .18 m away from each other. Each of the eight targets was associated with a number beginning with 1 (the target nearest the participant in the left radial arm) and increasing to 4 (the farthest target in the left radial arm). For the right radial arm, target 5 was the target nearest the participant and target 8 was the farthest target. All targets and target numbers were visible to the participant at all times.

As in previous experiments conducted in this laboratory, the manipulanda were common toilet plungers. These are convenient objects because they can be placed easily on targets and, as seen later in this article, they can be modified easily to change their mass. The two plungers used here were identical to one another. They each consisted of a wooden cylinder .51 m high and .0023 m in diameter with a sturdy rubber base, .15 m in diameter.

The required movement periods were indicated by metronome clicks. The three periods were .40 s, .48 s, and .68 s. I chose these periods because previous research has shown that people can accurately match the durations of their reaches to comparable prescribed periods (van der Wel, Fleckenstein, Jax, & Rosenbaum, 2007; van der Wel, Sternad, & Rosenbaum, 2010).

Design

I used a mixed factorial design that crossed two between-subject levels of object mass (unloaded vs. loaded) with two between-subject levels of constant task leaning (near vs. far), for a total of four between-subjects groups. Variations of the within-subjects factors—movement distance, required movement speed (distance with respect to driving period), and hand-use—were identical across the four groups. The masses of the plungers were .135 kg and 1.27 kg in the unloaded and loaded groups, respectively. The between-group levels of leaning were defined by the endpoint targets of the constant task, which were in the left radial arm for half the participants in each group and in the right radial arm for the other half of the participants in that group.

In the near leaning groups, the constant task was defined by endpoint targets 1 and 3 when it was on the left and by endpoint targets 5 and 7 when it was on the right (see Figure 1). In the far leaning groups, the constant task was defined by endpoint targets 2 and 4 when it was on the left and by endpoint targets 6 and 8 when it was on the right. In all groups the movement distance in the constant task was invariant (.42 m) for all trials, but the movement distance in the alternative task was varied (.21 m, .42 m, or .63 m). Each choice was made between the constant task and the alternative task, which was defined by one of six possible pairs of endpoint targets.

In the far leaning groups the constant task was never paired with an alternative task that was defined by targets 1 and 3 (when the alternative was on the left) or targets 2 and 4 (when it was on the right). This is because I originally focused on the leaning manipulation in terms of the constant task. However, as will be seen below, an appropriate analysis would also have to account for the leaning factor in the alternative task, whose far target occupied three different proximities to the body over the course of the experiment. I addressed this issue with a complimentary analysis that focused on the pooled probability that the alternative task was chosen. It should be noted that while the alternative tasks were not strictly identical between groups, they were the same for all participants within each group.

Procedure

After completing an informed consent form and the Edinburgh Handedness Inventory (Oldfield, 1971), the participant stood in front of the apparatus while the experimenter read the directions aloud. The experimenter then asked the participant to say in his or her own words what s/he would be doing. The experimenter made sure the participant understood the task requirements and then gave the participant six practice trials for familiarization. The actual experiment did not repeat any combinations of driving frequencies and target pairs presented during the practice session.

At the start of each trial, the experimenter read aloud the designated endpoints for the constant and alternative tasks and had the participant repeat them to ensure correct knowledge of the trial's task descriptions. Participants chose the constant task or the alternative task while listening to a metronome that specified the rate at which the movements were to be made: .40 s period, .48 s period, or.68 s period. The three periods were tested in separate blocks of six trials each. The metronome played from the beginning of the practice session until the end of the last trial within a block. The metronome was turned off between blocks, and the participant was then given a short rest. I pseudo-randomly presented the alternative task pairs in succession with one driving period. Then I presented the same task pairs in the same manner with a different period. The order of the period blocks was also random. In summary, there were three driving period blocks containing six trials each for a total of 18 trials experienced by each participant. The experiment lasted approximately 30 minutes.

Each back-and-forth movement was completed four times for a total of eight inter-target movements. The experimenter told each participant in advance that he or she would not be responsible for knowing when to stop. The experimenter always told the participant when to terminate his or her back-and-forth movements. At the end of each trial, the experimenter told the participant where to put the plunger for the next trial. I had the participant move the plunger to the starting location both for expediency and also because I did not want the experimenter's movements to influence the participant's subsequent action choices. Previous work in this laboratory has shown that such influences can occur (Santamaria & Rosenbaum, in revision).

Data Analysis

I performed two complimentary analyses. First, I calculated the pooled probability that the constant task was chosen with respect to both the driving period and required movement distance in the alternative task. Based on the premise that the probability of the constant task being chosen should have been high when the alternative task was more effortful, I took these probabilities as estimates of the effort associated with different tasks. This analysis allowed me to directly compare my results to those of Rosenbaum and Gaydos (2008), which showed that longer distances were judged to be more effortful. I plotted effort as a function of the driving periods because the present study extended the task-choice method by manipulating movement time. A goal of this analysis was to reveal whether effort depended on an interaction between required movement distance and required movement time, as would be indicated by curves with non-zero slopes.

In a second analysis, I pooled the probability of the alternative task being chosen with respect to the required speed of the alternative tasks. Because the alternative tasks in each group contained variations of all the manipulated factors (movement distance, required speed, momentum, leaning, and hand choice), this approach allowed me to combine the data of all four groups. I used this set of probabilities to find out how popular each response was, as has been done in earlier work in this lab (Zhang & Rosenbaum, 2008), and then to develop a statistical model of the determinants of response popularity. The idea here was that if certain responses were more popular than others, then they must have been judged to entail less effort.

Chapter 3

RESULTS

This section has two parts. In the first I report the outcomes of the first analysis, which concerned the pooled probability that the constant task was chosen by each group. Each group will be referred to with abbreviations that correspond to the location of the constant task and the mass of the objects experienced by that group. The group that had the near constant and unloaded objects will be referred to as NU, the group that had the far constant and unloaded objects will be referred to as FU, the group that had the near constant and loaded objects will be referred to as NL, and the group that had the far constant and loaded objects will be referred to as FL.

In the second section I will focus on the pooled probability that participants chose the alternative task (1 minus the probability of choosing the constant task). The pooling will be done across groups. In this section I will present a series of regression models designed to explain an ever-increasing proportion of the variance. For each model, the pooled likelihood that participants chose the alternative task will be plotted as a function of required speed, and the data points associated with each factor will be shifted to the right by an amount that reflects the extra theoretical cost of that factor. The points are shifted by the amount that maximizes the proportion of explained variance. This rightward shifting of points is the graphical analog of adding more terms to a linear regression model with positive coefficients applied to its terms. The statistical significance of each increase in proportion of explained variance will be assessed with an F-change statistic where appropriate. The F statistic will then be compared to the critical rejection criterion in the F distribution for one degree of freedom for the hypothesis and the degrees of freedom for the error, which in this case, owing to the large n (>20), is nominally infinite: $F(1,\infty) = 3.84$, $\alpha = .05$.

Constant Task

Figure 2 shows the choice data from the NU group pooled across all other factors except alternative movement distance (AD) and plotted as a function of driving period. Participants tended to choose tasks that entailed shorter movement distances. Consistent with the hypothesis that speed requirements were taken into account, however, movement costs in the NU group increased for far alternative distances (AD = .63 m) and decreased for short alternative distances (AD = .21 m) when the driving period was shortest (.40 s). Because the range of required speeds was greatest for the shortest movement periods (see Table 1), this finding suggests that participants' sensitivity to speed emerged when the differences in required speeds were most salient.

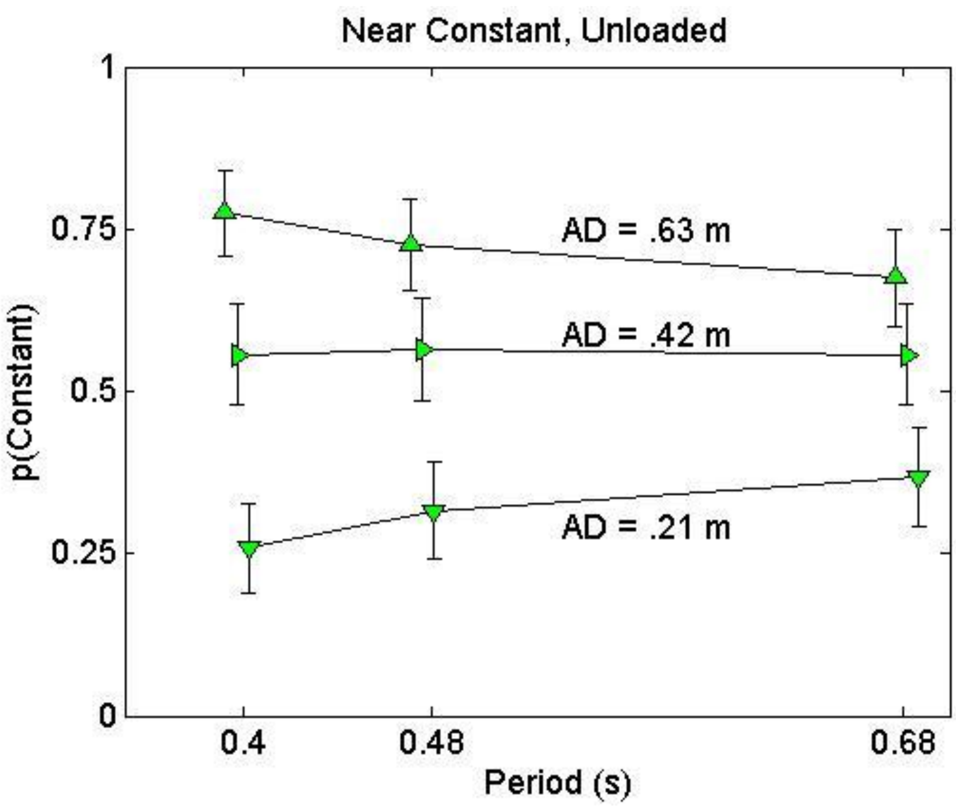

Figure 2. Pooled probability that the constant task was chosen across 40 participants in the *near, constant, unloaded* group plotted as cost functions of alternative task movement distance and driving period. Error bars represent ± 1 standard error of the binomial distribution.

Table 1

Required Speeds of the Constant and Alternative Tasks

	Movement Distance (m)	Driving Time Period (s)	Required Speed (m/s)
Constant task	.42	.68	.62
	.42	.48	.88
	.42	.40	1.05
Alternative task	.21	.68	.31
	.21	.48	.44
	.21	.40	.525
	.42	.68	.62
	.42	.48	.88
	.42	.40	1.05
	.63	.68	.93
	.63	.48	1.31
	.63	.40	1.58

The pooled FU data shown in Figure 3 indicate that participants again judged covering longer distances to be more costly than covering shorter distances. However, this pattern of results differed from the NU data in that there was a greater separation of the functions. The fact that the curves associated with the long and short distances migrated away from each other in the FU group as compared to the NU group suggests that participants in the FU group were more sensitive to movement distance.

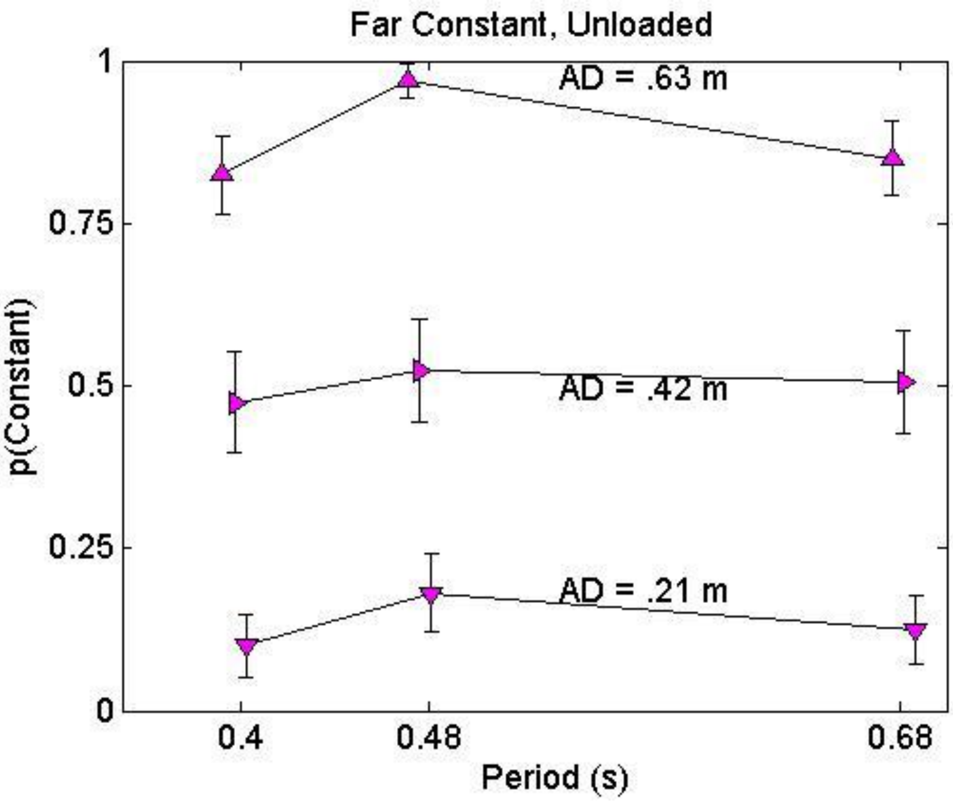

Figure 3. Pooled probability that the constant task was chosen across 40 participants in the *far constant, unloaded* group plotted as cost functions of alternative task movement distance and driving period. Error bars represent ± 1 standard error of the binomial distribution.

Much like the NU and FU groups, the NL group judged covering longer distances to be more costly than shorter distances (see Figure 4). Similar to the FU group, the choice data of the pooled NL groups reflected a higher sensitivity to movement distance, as indicated by the greater separation of the effort functions relative to the NU group. Another notable feature of the NL group's data is a slight upward shift in all the effort curves relative to the curves in the NU group. This outcome is consistent with the hypothesis that participants were sensitive to the increases in object mass, which in turn, may have increased perceived effort.

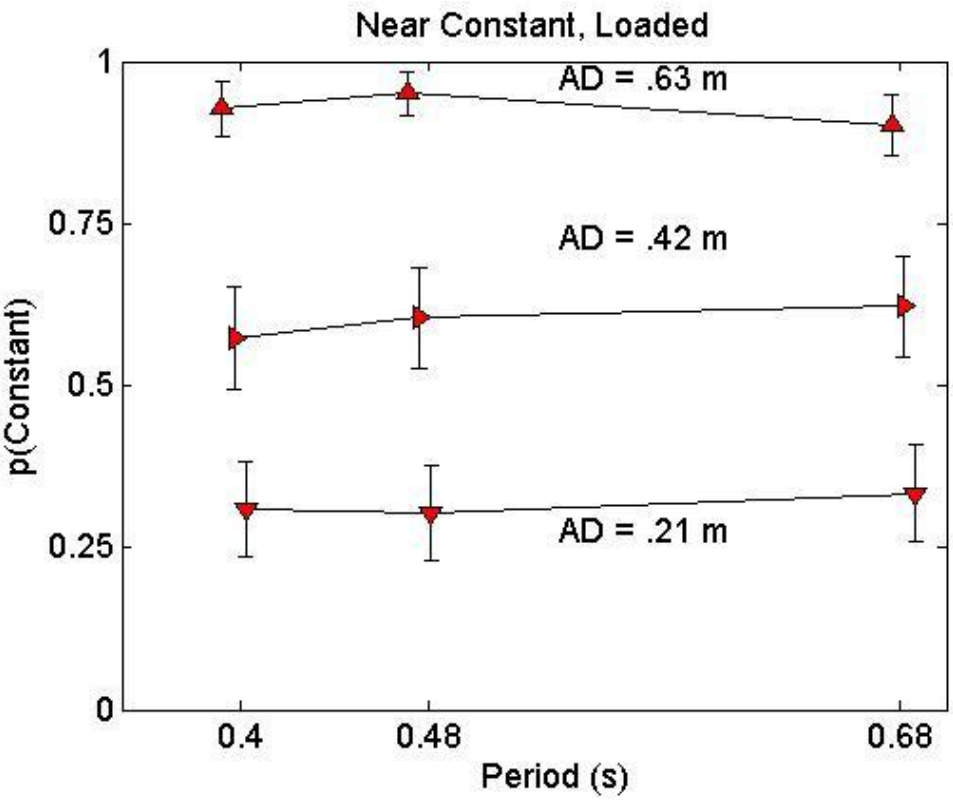

Figure 4. Pooled probability that the constant task was chosen across 39 participants in the *near constant, loaded* group plotted as cost functions of alternative task movement distance and driving period. Error bars represent ± 1 standard error of the binomial distribution.

Figure 5 shows the pooled choice data from the FL group. As in the other groups, participants in the FL group judged covering longer distances as more costly than shorter distances. The effort functions for the FL group were similar to those for the FU group, suggesting that the added loads did not have a significant impact on effort when the constant task was far away.

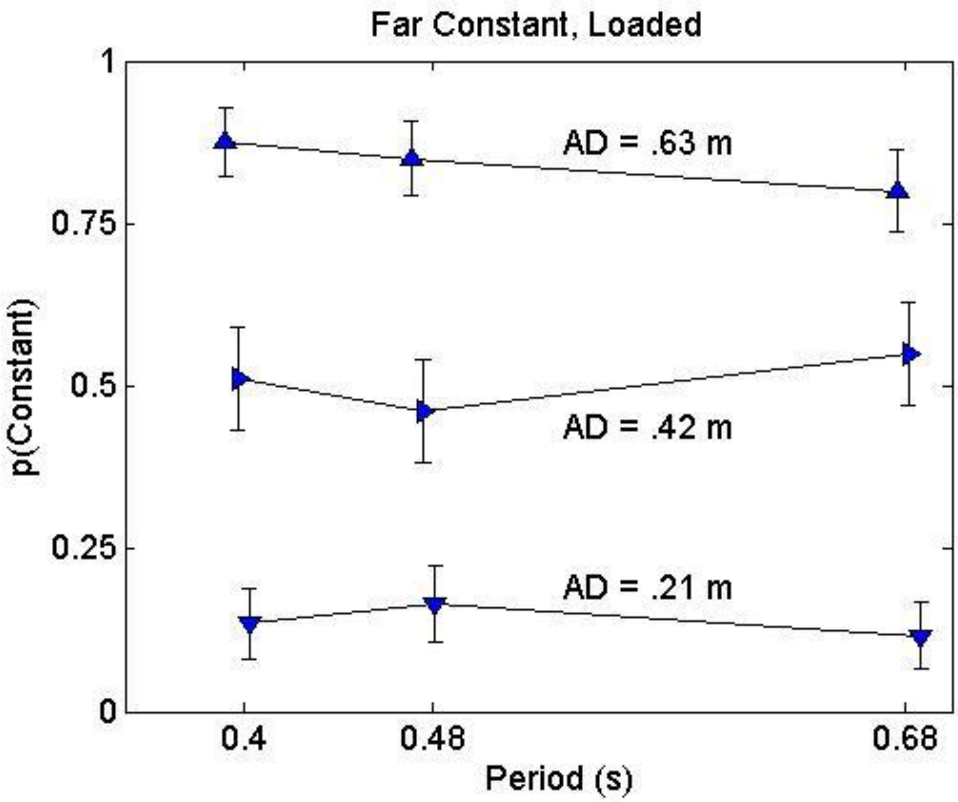

Figure 5. Pooled probability that the constant task was chosen across 41 participants in the *far constant, loaded* group plotted as cost functions of alternative task movement distance and driving period. Error bars represent ± 1 standard error of the binomial distribution.

Alternative Task

The previous section focused on the pooled probability that the constant task was chosen. This section focuses on the pooled likelihood that the alternative task was chosen. The higher this likelihood, the more popular the alternative task was. The section starts by reporting the influence of movement distance and then introduces other factors that successively contributed less and less to the popularity of the alternative task.

I first plotted the pooled likelihood that participants chose the alternative response with respect to the movement distance of the alternative task and which hand performed the task. Figure 6 shows the 72 relevant data points (18 from each of the 4 groups) pooled across all factors except required alternative distance and hand choice. Because these data were plotted with respect to a dimension of the alternative task, high values indicate that those tasks were more popular and so, by assumption, less effortful. Consistent with my initial analysis, Figure 6 shows that task popularity generally decreased as movement distance increased.

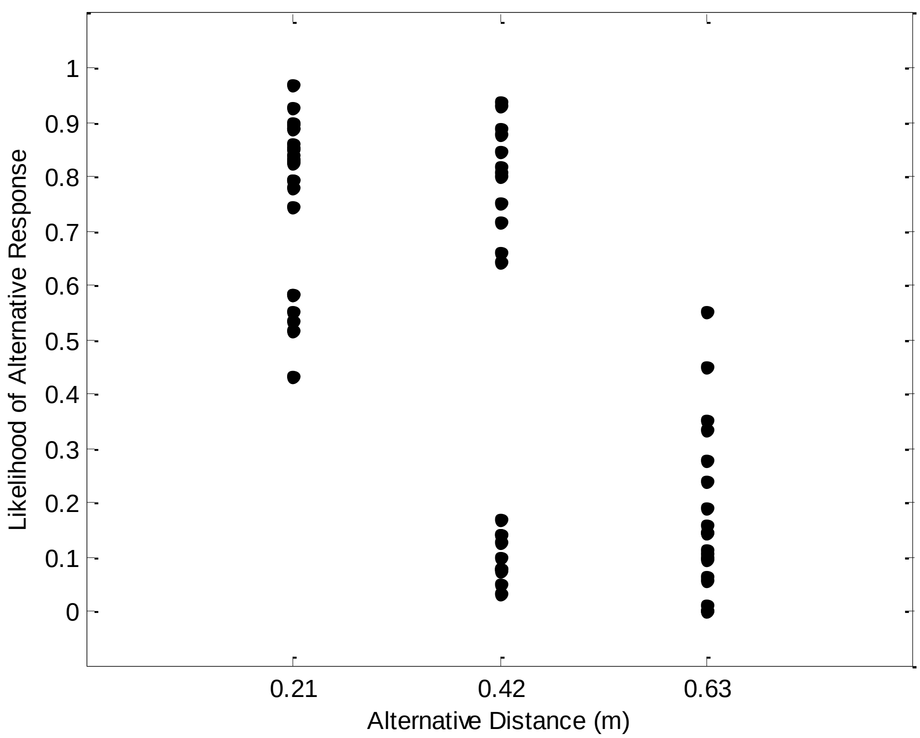

Figure 6. Pooled likelihood that the alternative task was chosen plotted with respect to hand-use and movement distance of the alternative task. Data are pooled across all groups.

Next, I considered how these task popularity estimates varied as a function of movement distance *and* required movement time. Figure 7 shows the data from Figure 6 replotted as a function of required speed (distance divided by required movement time, ignoring the difference between outgoing and ingoing directions). Replotting the data this way yielded a richer, more useful distribution of estimates because the alternative tasks afforded nine unique speeds, whereas the constant tasks afforded only three.

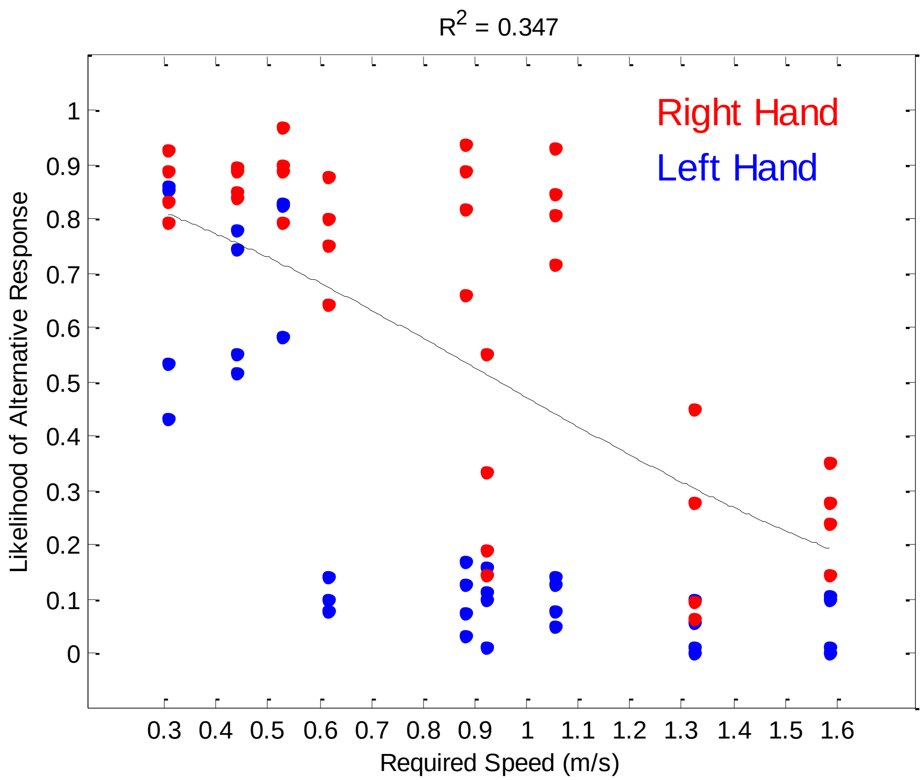

Figure 7. Pooled likelihood that the alternative task was chosen plotted with respect to hand-use and required speed of the alternative task. Data are pooled across all groups.

As can be seen in Figure 7, task popularity decreased in an orderly way as required speed increased. Because this decrease in task popularity followed an S-shape, I fitted these data with a curve generated by the mathematical function of 1 minus the cumulative distribution function (1-CDF) of the standard normal distribution. This function is convenient because, canonically, it has a fixed mean and standard deviation (with values of 0 and 1, respectively). Because I horizontally centered the curve at the median value of required speed, the only free parameter for this fit was the number of standard deviations above and below the mean (θ) that were used to generate the curve. For the curve shown in Figure 7, a value of θ = .88 minimized the sum of squared deviations between the 72 pairs of observed and predicted values. The proportion of variance explained was R^2_{speed} =.347. This value was given by $R^2_{speed} = [1-(SS_{err}/SS_{tot})]$

where SS_{err} was the residual sum of squared deviations, and SS_{tot} was the total sum of squared deviations. The R^2 values reported below were computed the same way.

To assess the statistical significance of this effect size, I computed an F-change statistic that compared the value of R^2_{speed} (.347) to the value of R^2_{null} (0.00) predicted by a null model with zero predictors. The F statistic was $F = [(R^2_{speed}-R^2_{null})/(k_{speed} - p_{null})]/[(1-R^2_{speed})/(n-(k_{speed} + 1))]$, where k_{speed} was the number of predictors in the speed model, p_{null} was the number of predictors in the null model, and n was the number of data points. The values of k_{speed}, $p_{null,}$ and n were 1, 0, and 72, respectively. The F value associated with the increase from R^2_{null} (0.00) to R^2_{speed} (.347) for the speed model was $F(1, 70)= 37.2$, $p<.001$.

Next, I asked whether the goodness of fit of the S-shaped function could be improved by expressing the cost of using the non-preferred hand as an increase in required speed. Figure 8 shows the data with each of the left-hand points shifted to the right. This shift transformed the x-axis from required speed (υ) into functional required speed, $\varphi = \upsilon + \beta(\lambda_L + \lambda_R)$, where β was the coefficient that, when multiplied by fixed parameters for the left hand ($\lambda_L = 1$) and right hand ($\lambda_R = 0$), shifted the blue points to yield the best-fitting curve generated by the 1-CDF function. Here the estimates of β and θ_{hand} were .710 and 1.80, respectively. The overall proportion of explained variance increased from $R^2_{speed} = .347$ to $R^2_{speed+hand} =.656$, indicating that the variance accounted for by hand choice was $R^2_{hand} = .309$. This change in overall R^2 was statistically significant $F(1, 69) = 26.06$, $p < .001$, as indicated by the equation $F = [(R^2_{speed+hand}-R^2_{speed})/(k_{speed+hand} - p_{speed})]/[(1-R^2_{speed+hand})/(n-(k_{speed+hand} + 1))]$, where $k_{speed+hand}$ was the number of variables in the speed and hand model, p_{speed} was the number of variables in the speed model, and n was the number of data points. The values of $k_{speed+hand}$, p_{speed}, and n were 2, 1, and 72, respectively.

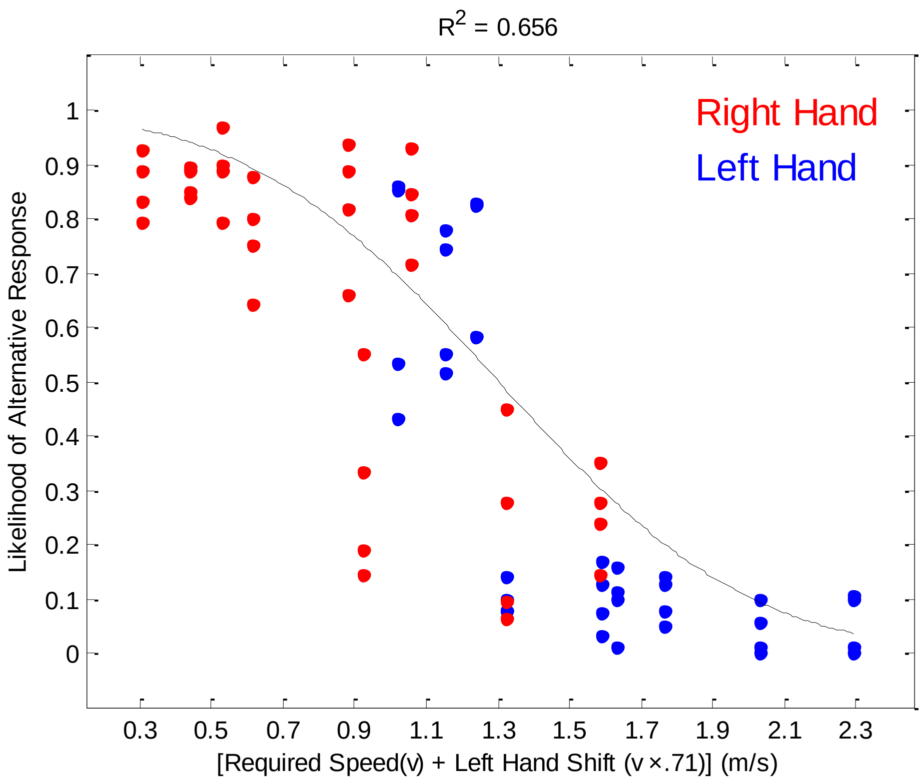

Figure 8. Pooled likelihood that the alternative task was chosen plotted with respect to hand-use and functional required speed of the alternative task. Left hand points are shifted to the right relative to Figure 7. Data are pooled across groups.

My next step was to estimate the effect of leaning. Figure 9 shows the hand-shifted data with all the points expanded with respect to low (*L*), medium (*M*), and high (*H*) leaning indices and shifted even further to the right. The figure depicts 132 points, each of which is labeled with either an *L*, *M*, or *H*. The low (*L*), medium (*M*), and high (*H*) leaning indices correspond to alternative tasks whose far targets occupied targets 2 or 6, targets 3 or 7, and targets 4 or 8, respectively (see Figure 1). There are 132 points because the calculation of the likelihood that participants chose the alternative response [1-p(constant)] with respect to leaning yielded 18 points in each of the NU and NL groups: 3 points for the longest movement distance because that pair of targets always had a high leaning index, 6 points for the intermediate movement distance because those pairs of targets had either a high or medium leaning index, and 9 points for the shortest movement distance because those pairs of targets had either a high, medium, or low leaning index. These points were doubled when the probabilities were also calculated with respect to hand use. In sum, the NU and NL groups contributed 72 points to Figure 9. The FU and FL groups contributed 60 points to Figure 9. The FU and FL groups contributed fewer points because participants in those groups never had the opportunity to choose an alternative task with an intermediate movement distance that had a medium leaning index (see Table 2). Thus, the calculation of the likelihood that participants made the alternative response with respect to leaning yielded only 15 points in each of the FU and FL groups. The number of these points doubled when the probabilities were calculated with respect to hand.

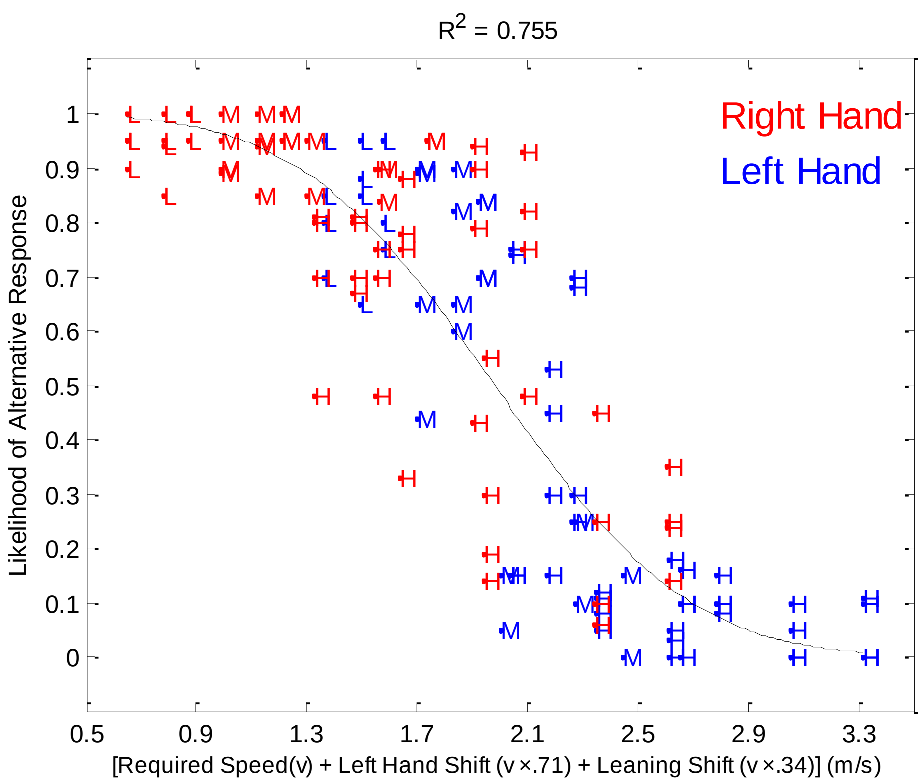

Figure 9. Pooled likelihood that the alternative task was chosen plotted with respect to leaning, hand-use, and required speed of the alternative task. All points are shifted to the right relative to Figure 8. Data are pooled across groups.

Table 2

Movement Endpoint Target Pairs for the Constant and Alternative Tasks

Groups	Constant task	Alternative task
Near Constant, Unloaded (NU)	[1,3]	[5,6] [5,7] [5,8] [6,7] [6,8] [7,8]
Near Constant, Loaded (NL)	[5,7]	[1,2] [1,3] [1,4] [2,3] [2,4] [3,4]
Far Constant, Unloaded (FU)	[2,4]	[5,6] [5,8] [6,7] [6,8] [7,8]
Far Constant, Loaded (FL)	[6,8]	[1,2] [1,4] [2,3] [2,4] [3,4]

Note. Half of the participants in each of the four groups received the constant task on the left. Endpoint targets 1-4 correspond with tasks presented on the left (see Figure 1). Endpoint targets 5-8 correspond with tasks presented on the right (see Figure 1).

The shifts in x-axis values for the leaning analysis represented functional required speed given by $\varphi = \upsilon + \beta(\lambda + \omega) + \beta_{leaning}(L + M + H)$. The curve shown in Figure 9 was generated by the best-fitting (1-CDF) function where $\beta_{leaning} = .340$ and $\theta_{leaning} = 2.40$. The fixed parameters for the leaning indices were $L = 1$, $M = 2$, and $H = 3$. The proportion of variance explained increased from $R^2_{speed+hand} = .656$ to $R^2_{speed+hand+leaning} = .755$, indicating that the proportion of variance explained by leaning was $R^2_{leaning} = .099$.

Because the foregoing estimation of the effect for leaning required the consideration 132 data points, and the estimation of the effect for hand choice required the consideration of only 72 points, I could not use the F-change statistic because it is assumed for this statistic that the degrees of freedom in the model containing more variables is less than the degrees of freedom in the model containing fewer variables. To address this issue I used a different method to evaluate the significance of leaning cost. I reasoned that if leaning significantly influenced the likelihood of the alternative response, then the *L*s should populate the top of Figure10, the *M*s should populate the middle, and the *H*s should populate the bottom. Another way of expressing this is to say that there should be few violations of monotonicity in leaning indices ($L = 1$, $M = 2$, $H = 3$) proceeding from more popular to less popular tasks.

To test this prediction, I paired each data point with its respective leaning index and ordered those pairs from highest popularity to lowest. I then calculated the number of observed monotonicity violations in the leaning indices. The number of observed monotonicities was 19. Then I wrote a MATLAB program (Mathworks, Inc., Natick, MA) to randomly reorder the pairs 10,000 times, and I calculated the number of monotonicity violations generated by the simulation on each iteration. Figure 10 shows that the number of violations I observed (indicated by the arrow) was far less than the any number of violations in the distribution generated by the simulation. This outcome suggests that the number of monotonicity violations I observed in the choice data was far less than what would be expected by chance alone.

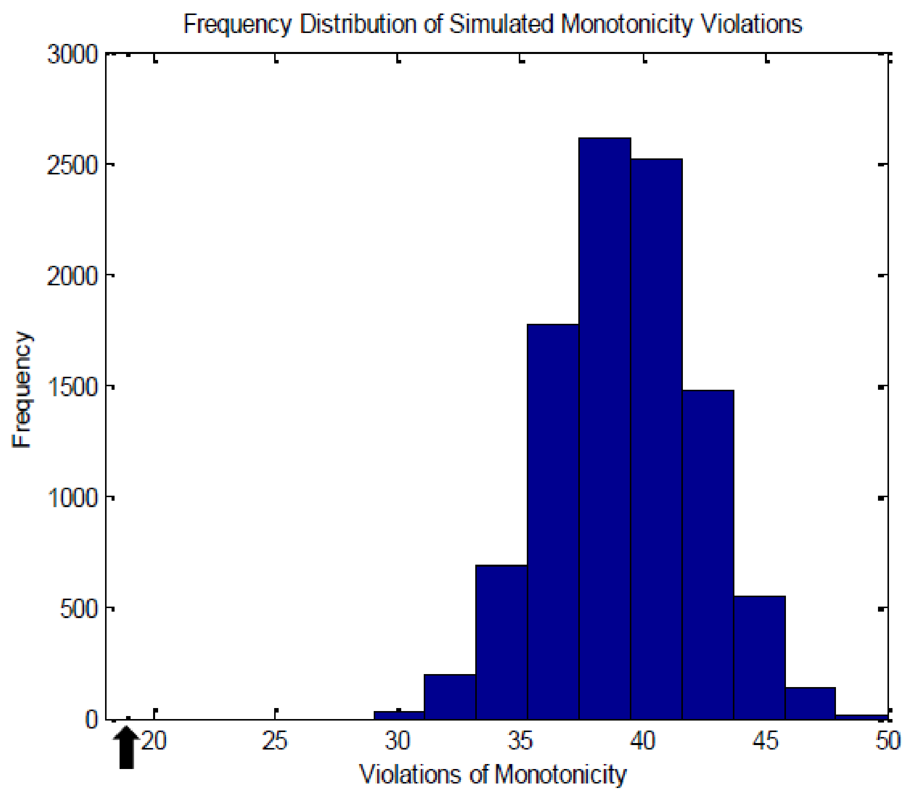

Figure 10. Frequency distributions of the number of simulated monotonicity violations in the ordered leaning indices. Arrow indicates the number of observed violations in the pooled likelihood of the alternative response data (19).

A caveat is in order about the latter test. Because some alternative tasks combined short displacement distances with high leaning indices and because tasks with long distances always had high leaning indices, the extent to which the observed monotonicity violations reflect a preference for shorter movement distances rather than lower degrees of leaning is unclear. I addressed this issue by performing a second simulation that was identical to the first except it only considered alternative tasks with the shortest possible movement distance. As shown in Figure 11, the results of the second simulation were similar to the results of the first. The number of observed monotonicity violations was 13 (indicated by arrow), a number much lower than the number of violations expected by chance alone. Taken together, these results suggest that leaning cost significantly influenced task popularity.

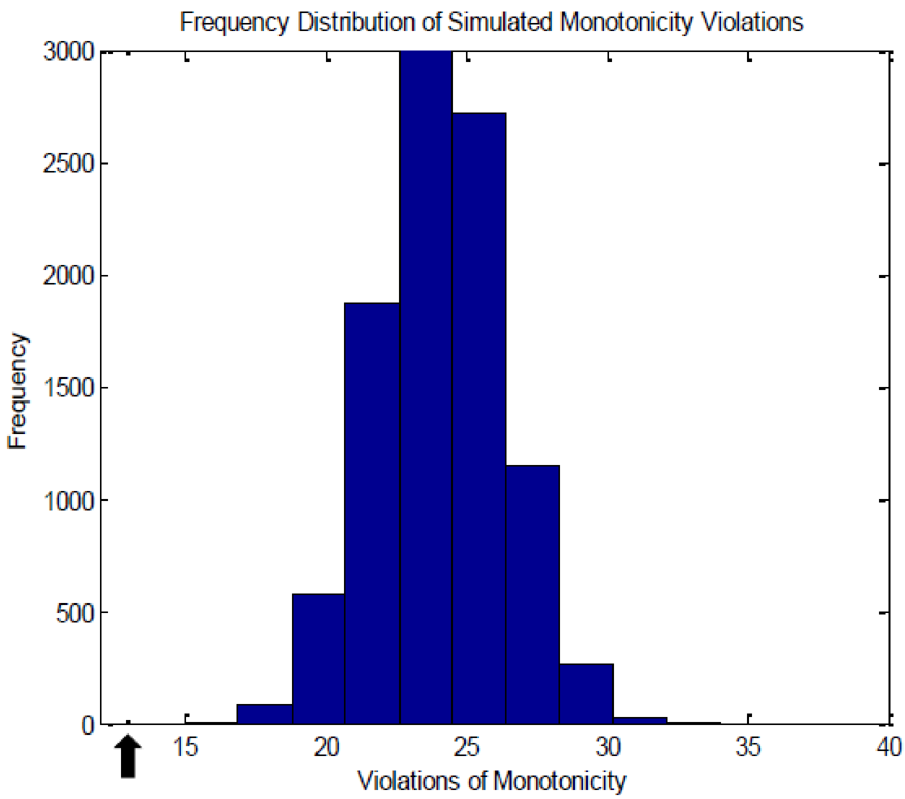

Figure 11. Frequency distributions of the number of simulated monotonicity violations in the ordered leaning indices for tasks with the shortest movement distance. Arrow indicates the number of observed violations in the pooled likelihood of the alternative response data (13).

My final step in this analysis was to estimate the effect of momentum. Recall that the objects were equally weighted in the loaded groups. As a result, I did not expect task popularity to vary as a function of whether the tasks entailed loaded objects because a given participant never had the opportunity to choose objects of different mass. Consistent with this expectation, the overall R^2 did not increase when I applied different values of $\beta_{momentum}$ to the fixed parameters that I assigned to the unloaded objects ($\Theta = 0$) and loaded objects ($\sigma = 1$). However, there was evidence to suggest that momentum requirements interacted with leaning requirements such that participants more frequently avoided tasks with high leaning indices when the objects were loaded. As shown in Figure 4, the curve associated with the longest alternative movement distance (AD =.63 cm) for the NL group shifted upward compared to the corresponding curve for the NU group. Likewise, the curve associated with the shortest alternative movement distance (AD = .21 cm) was also shifted upward for the NL group compared to the NU group, which likely also reflects a greater sensitivity to leaning because the tasks with short distances sometimes had high leaning indices.

To assess whether this interaction could explain any variance in the popularity of the alternative response, I applied different values of $\beta_{momentum}$ to the leaning indices of the data points associated with the tasks performed with the loaded objects. Figure 12 shows the loaded data points shifted a bit further to the right so that the x-axis was given by $\varphi = \upsilon + \beta_{hand}(\lambda + \omega) + \beta_{leaning}(L + M + H) + \beta_{momentum}(L_l + M_l + H_l)$. The indices for tasks that involved loaded objects are denoted as L_l, M_l, and H_l. The β value that resulted in the best-fitting 1-CDF function was $\beta_{momentum}$=.028 with a corresponding θ value of $\theta_{momentum}$=2.48. The percentage of variance explained increased from $R^2_{speed+hand+leaning} = .755$ to $R^2_{speed+hand+leaning+momentum} = .760$, indicating that the proportion of variance accounted for by momentum was just $R^2_{momentum} = .005$. This increase in overall R^2 was not significant, $F(1, 130) = 2.709$, $p>.05$. The implication is that although mass increases may have affected perceived effort in the NL group, as indicated by my analysis concerning the constant task, the added loads did not significantly influence overall task popularity.

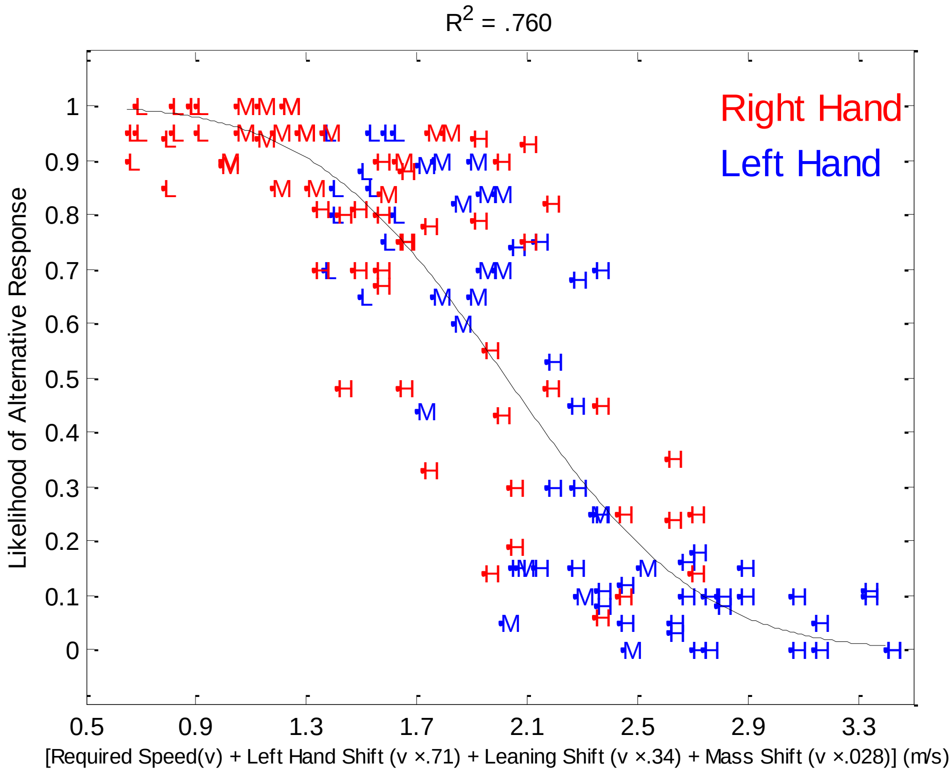

Figure 12. Pooled likelihood that the alternative task was chosen plotted with respect to leaning, hand-use, and functional required speed of the alternative task. Only the points that represent tasks performed with loaded objects are shifted to the right relative to Figure 9. Data are pooled across groups.

Chapter 4

DISCUSSION

The purpose of this study was to characterize movement-related effort. Theories of movement planning assume that people generate less effortful rather than more effortful actions (Erlhagen & Schöner, 2002; Rosenbaum et al. , 2001; Sparrow & Newell, 1998; Todorov, 2004). However, establishing a method for estimating movement-related effort is still in its infancy (Rosenbaum & Gaydos, 2008). I sought to contribute to the development of such a method by extending the task-choice method of Rosenbaum and Gaydos (2008). These researchers used the task-choice method to show that the effort of moving objects increased with higher degrees of required translation. Here I extended the method by asking if movement distance alone accounts for these preferences or whether required speed, hand-use, leaning, and load also do so.

On each experimental trial, I gave participants two possible back-and-forth object displacement tasks, one of which was constant for any given participant. I asked participants to perform whichever task seemed easier. Then I used the pooled probabilities of choosing the constant task to estimate effort in each experimental group. In a complimentary analysis, I calculated the pooled probability of choosing the alternative task over groups, treating that pooled probability as a measure of task popularity (the lower the popularity, the greater the judged relative effort). I used regression models to predict task popularity. The regression models captured an ever-increasing proportion of variance. Each successive model expressed the cost of a factor as an increase in a single putative currency -- required speed. The complete model showed that required speed, non-preferred hand use, and leaning all contributed significantly to task popularity.

The remainder of this discussion is organized into sections that address each factor. In the first section, I argue that the task-choice method is both reliable and flexible. In the second section, I conclude that my participants tried to minimize (unsigned) distance with respect to time (speed). I note that although required speed appeared to influence effort, speed was not the only factor that contributed to task popularity. Consistent with this interpretation, I highlight in the third section that leaning was also important. In subsequent sections, I discuss possible explanations for why participants in the current study did not seem especially sensitive to momentum, and I discuss some caveats associated with the current findings. Finally, I raise questions for future research.

Movement Distance

One of the clearest results of this study was that longer movement distances are associated with more effort. In all groups, participants tended to choose the constant task when the alternative task entailed a longer movement distance (see Figures 2, 3, 4, and 5). Conversely, participants preferred the alternative task when the constant task entailed a longer distance. These results agree with the results of Rosenbaum and Gaydos (2008), suggesting that the task-choice method is reliable for estimating effort in reaching and grasping tasks.

The fact that participants in the present study judged longer distances to be more effortful also indicates that the task-choice method is flexible. Recall that the method used here entailed a constant task, whereas the method used by Rosenbaum and Gaydos (2008) did not. This modification allowed a clearer assessment of how changes in one task can modulate choices. For example, an increased constant task leaning requirement in the FU group seemed to make participants more sensitive to alternative movement distance. This conclusion is based on the observation that the effort curve associated with the longest distance in the FU group was higher relative to the NU group, whereas the short distance curve was lower (see Figures 2 and 3). This result can be explained by the fact that the constant task in the FU group had the same leaning requirement of the alternative task when the alternative distance was longest. Thus, participants did not have to negotiate a difference between leaning costs when the constant task was paired with an alternative task with the longest possible distance. In response to this situation, participants preferred the task with the shorter distance (i.e., the constant task). By contrast, the leaning requirement of the alternative task was never greater than the leaning requirement of the constant task when the alternative distance was short. Thus, the FU group preferred the alternative tasks more (and the constant task less) when the alternatives had shorter distances.

The findings just discussed indicate that the task-choice method is flexible enough to accommodate useful modifications, including, most importantly, assessment of the relative costs of multiple factors. For instance, the fact that the slopes of the curves shown in Figures 2, 3, 4, and 5 are not zero in all cases suggests that participants were also sensitive to required movement time. The next section discusses the possibility that participants were sensitive to a ratio of distance to time (speed).

Required Speed

If one assumes that the participants in the Rosenbaum and Gaydos (2008) study tried to complete each task within a roughly constant time period, then it is possible that the preferences to move across shorter movement distances reflected preferences to move at slower speeds. I tested this hypothesis (which does not depend on the latter specific assumption) by imposing timing requirements on a number of tasks that entailed different distances. My reasoning was that if choices reflected sensitivities to both movement distance and time, participants would prefer tasks with lower speeds.

As mentioned above, Figures 2, 3, 4, and 5 provide initial support for the notion that participants were sensitive to both movement distance and movement time because some of the curves had nonzero slopes. More direct support for this conclusion came from the analysis of the pooled likelihood that the alternative task was chosen. Figure 7 shows that the popularity of the alternative tasks decreased in an orderly manner as required speed increased. Required speed explained a significant proportion of variance in task popularity, as indicated by the best fitting S-shaped function (1-CDF). Given this outcome, it should be useful to interpret the best-fitting free parameter (θ). The fact that θ was only 0.88 indicates that the transition from high popularity estimates to low popularity estimates was gradual, suggesting that although task popularity depended on required speed, participants were also sensitive to other factors.

These observations accord with previous research showing that sensitivity to the duration of potential movements can be influenced by other task features (Young, Pratt, & Chau, 2008; 2009). Young et al. (2008) asked participants to indicate which of two possible reaching tasks afforded the shorter movement time. Because Fitts' Law holds that higher indices of difficulty (ID) are associated with longer movement times (Fitts, 1954), Young et al. expected participants to choose the task with the lower ID on each trial. Consistent with the notion that people are sensitive to the durations of potential actions, participants in the Young et al. study performed the discrimination task well. However, closer targets sometimes biased participants away from the task with the lower ID. When these results are viewed in light of the current findings, it seems clear that people are sensitive to both movement distance and movement duration.

If people are sensitive to multiple factors, then one would expect to find that other costs influenced task popularity in the current study. Indeed, the cost of using the non-preferred hand also explained a significant proportion of variance in task popularity. The relations between task popularity, required speed, and hand-choice are addressed next.

Hand-Choice

Hand-use requirements influenced task popularity. This conclusion is supported by the fact that tasks that could only be performed with the left hand were less popular than tasks that could only be performed with the right hand (see Figure 7). Moreover, the regression model that included hand choice explained a significant proportion of variance (see Figure 8), providing further evidence that participants ascribed more effort to moving the non-preferred hand relative to the preferred hand. This observation raises the question of how much additional effort participants ascribed to the left hand. The model described above provides one possible answer to this question.

The fact that the best-fitting coefficient (β) in the model was .710 suggests that using the nonpreferred hand costs much the same as moving at an additional .710 times any given required speed. This claim should be qualified by the fact that in order to obtain β, I had to arbitrarily assign fixed parameter values to the hand left hand (λ_L =1) and to the right hand (λ_R =0). Importantly, the proportion of variance explained by hand choice would not change if λ_L and λ_R took different positive values, so long as those values preserved the same interval relationship. However, because different fixed parameters could change the amount of increased functional speed associated with the points, I do not attach any particular significance to the absolute magnitude of β, nor do I intend to assign special meaning to the absolute magnitudes of β obtained from the estimations of effect sizes for the other factors.

Despite the caveat just given, the relative magnitudes of β obtained for each factor may be meaningful because the fixed parameters used in each model were similar. Since a higher value of β would correspond to a greater rightward shift in the points, a higher value of β would also mean that there was more systematic variance of task popularity related to that factor. In other words, there would be a clear gradation of fixed parameter values associated with the transition from high task popularity to low task popularity. Thus, higher relative values of β indicate that the model explained greater amounts of variance with the S-shaped curve. As mentioned above, the best-fitting value of β for the model that included required speed and hand choice was .710, a value greater than the best fitting coefficients for leaning (β = .34) and momentum (β = .028). These comparisons suggest that hand-choice was one of the most influential factors.

It should also be useful to interpret the best-fitting value of θ. For the model represented in Figure 8, the best-fitting value of θ_{hand} was 1.80. This value is more than two times greater than the value of θ obtained in the model that only entailed required speed (θ = 0.88), suggesting that participants were much more decisive when they considered both hand-use requirements and required speed, rather than when they considered required speed alone. Interestingly, this sensitivity seemed to emerge in the presence of higher required speeds. Figure 7 shows a greater vertical spread between the left hand points and the right hand points for required speeds above .525 m/s, indicating that participants were especially reluctant to use the non-preferred hand if they had to move it quickly.

The findings just discussed agree with a large body of research showing that manual asymmetries are prominent features of human behavior that may contribute to handedness (Carey et al., 1996; Carson, 1993; Elliot et al.; Flowers, 1975; Healy et al.; Helbig & Gabbard, 2004; Mamolo et al., 2004; Peters, 1995; Sainburg, 2002; Sainburg & Kalakanis, 2000). Because handedness is commonly assessed as the preference to use a certain hand for most unimanual tasks, it remains important to determine the factors that drive hand preference. The current finding that the effort of using the non-dominant hand is especially salient in the presence of higher required speeds is consistent with previous research showing that people tend to prefer the dominant hand when accuracy demands are high (Bryden & Roy, 2006). Because movements tend to be less accurate at higher speeds (Fitts, 1954), it is possible that participants in the current study thought using the dominant hand would attenuate error increases at higher speeds.

Interestingly, other research has shown that the non-dominant hand can achieve temporal and spatial accuracy equivalent to the dominant hand and can even perform better in some situations (Sainburg, 2002; Sainburg & Kalakanis, 2000; Sainburg & Wang, 2002). These studies suggest that although accuracy seems important for determining hand selection, it cannot fully explain why participants seem to ascribe more effort to non-dominant hand use. Nonetheless, a limitation of the current study is that it does not provide the timing accuracy of the movements participants made. Thus, it is not possible from the present data to determine the extent to which the observed dominant hand bias related to the quality of performance. It will be important for future work to address the relations between factors that influence perceived effort and factors that influence temporal accuracy.

Previous research supports the idea that effort is linked to spatial accuracy. Rosenbaum and Gregory (2002) found that participants judged shorter movements that produced large jumps in a cursor (high gain) to be more effortful than long movements that produced small cursor jumps (low gain). Because participants were less accurate in the high gain conditions, Rosenbaum and Gregory suggested that effort ratings reflected the difficulty of achieving desired spatial precision. If temporal accuracy is also related to effort, then one would expect back-and-forth tasks that afford less variability to be more popular. This hypothesis is consistent with previous research suggesting that movement planning depends on neuromotor variability (see Davidson & Wolpert, 2005, for a review).

The current findings concerning hand-choice indicate that psychophysical movement costs are not constant across the hemisphere/limb systems. Rather, people seem to negotiate the differences between the dominant and non-dominant hands when ascribing costs to potential movements. These results also demonstrate the ability of the task-choice method to reveal how effort varies across hands. This feature of the method may be useful for elucidating the mechanisms underlying hand preference and, more generally, for developing theories of handedness that posit unique performance specializations for each hemisphere/limb system (e.g., Sainburg, 2002).

Leaning

Participants in the present study were also sensitive to greater degrees of leaning. The data from the FU group (see Figure 3) show that an increase in the leaning demand of the constant task was associated with an increase in sensitivity to movement distance relative to the NU group (see Figure 2). As argued above, this effect probably emerged because a far constant task meant that participants did not have to negotiate differences in leaning demands as often. In turn, this may have resulted in a greater separation of the effort functions. Consistent with this interpretation, a similar pattern can be seen in the FL group where the constant task was also farther away from participants (see Figure 5).

More direct evidence for the influence of leaning comes from the results of the regression model that considered the relations between leaning and the popularity of the alternative task. As shown in Figure 9, tasks with higher leaning indices tended to be less popular. Moreover, the regression model that expressed the cost of leaning as an increase in required speed confirmed that leaning had a significant impact on task popularity. This model explained a greater amount of variance than did the model that only included speed and hand-choice. The best-fitting coefficient that determined the magnitude of the shift ($\beta_{leaning}$) was .340. This value indicates that a one-unit increase in leaning index (*L* = 1, *M* = 2, and *H* = 3) costs much the same as moving at an additional .340 times the current functional required speed. Although this claim is qualified by the fact that the fixed indices were arbitrarily assigned, $\beta_{leaning}$ was the second largest coefficient obtained in the current study. Furthermore, the best-fitting value of $\theta_{leaning}$ was 2.40, suggesting that participants were even more decisive when they considered leaning, hand-use requirements and required speed, compared to when they only consider hand-choice and required speed. These outcomes support the idea that leaning played a significant role in determining task popularity.

Another important result was that the transition between high task popularity values and low task popularity values was associated with a low number of non-monotonicities in leaning indices. The number of observed monotonicity violations was lower than what would be expected by chance alone (see Figure 10). Moreover, this relationship persisted even when the analysis only considered tasks with the same movement distance (AD = .21 m; see Figure 11), providing yet more evidence that participants ascribed effort to leaning.

These findings are consistent with research showing that people plan for postural control by making anticipatory postural adjustments (APAs) before the onset of upper and lower limb voluntary movements (Belenki, Gurfinkel and Paltsev, 1967; Bouisset and Zattara, 1987; Gelfand, Gurfinkel, Tsetlin, and Shik, 1966). Moreover, Belenki et al. (1967) used electromyographic (EMG) recordings and center of force (COF) projections to show that APAs are specific to subsequent movements. Given the importance of postural control during standing and reaching tasks, future research could also address the specific physiological and biomechanical effects of the manipulations used in the current study. One useful effect to address can be seen in the data from the NU group (see Figure 2), which reflect a particular kind of sensitivity to speed that was not observed in the FU group. Rather, this sensitivity seemed to be attenuated when leaning demands of the constant task were increased. This pattern of results may be predicted by a minimum energy cost model (cf. Alexander, 1997) based on a simple cantilever model of the standing human body (see Figure 13). This model poses two energy costs, one associated with the trunk (E_p) that is proportional to the trunk angle and the velocity of the center of mass (COM), and another associated with the movement of the arm (E_m) that is proportional to the hand velocity and elbow joint angle. The trunk angle would be greater for leaning postures than for more upright postures while the COM velocity would stay roughly the same because the reaching tasks would require participants to stand in the same location, as they did in the present study. Likewise, E_m would be approximately constant across all the reaching tasks. Thus, the postural energy cost would grow with increasing forward leaning demands, but the limb movement energy cost would not. Such a model may also be useful for studying the increased sensitivity to movement distance I observed in the FU group, which may have reflected participants' attempts to minimize this postural stability cost. This is one simple suggestion for future work on biomechanically modeling the findings I have obtained. Other models may be better suited for this goal, but additional research will be needed to address this opportunity.

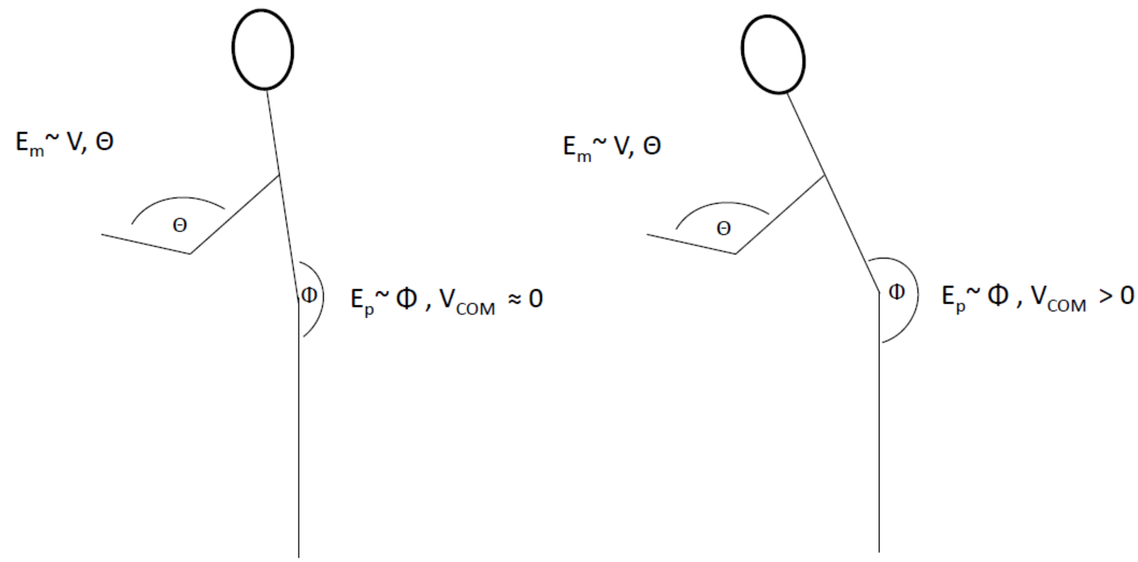

Figure 13. A simple biomechanical model that assumes equal arm movement energy costs (E_m), proportional to elbow joint angle (Θ) and hand velocity (v), for upright and forward leaning postures. The model claims that participants become more sensitive to leaning and less sensitive to E_m via an increase in postural energy cost (E_p), which is proportional to trunk angle (Φ) and center of mass velocity (v_{COM}).

Momentum

The momentum of an object is given by its mass times its velocity. As a result, changes in momentum are proportional to the forces required to move the object at different rates (Winter, 1990). Because an overarching goal of this study was to reveal whether the effort of translocation tasks depends on required speed, it was important to assess whether changes in object mass modulated effort. To test for this effect, I added an equal load to each task in the NL and FL groups. As mentioned above, I did not expect task popularity to vary strictly as a function of whether the tasks entailed loaded objects because a given participant never had the opportunity to choose a task with a different mass than the paired alternative. Nonetheless, the analysis of the pooled probability that the constant task was chosen yielded some telling results in the NL group. As shown in Figure 4, the curves have separations similar to those observed in the FU group (see Figure 3). However, this result cannot be attributed solely to an increased sensitivity to movement distance, as I argued was the case in the FU group. If this separation was driven only by movement distance, then the curve associated with the longest distance (AD = .63 m) would have shifted upward and the shortest distance curve (AD = .21 m) would have shifted downward, as they did in the FU group. As can be seen in Figure 8, this was not the case in the NL group. Rather, the short distance curve also shifted upwards, suggesting that choices there reflected sensitivity to a different factor. The most likely factors underlying this effect were the medium and high leaning demands in the alternative tasks with the shortest distance. Consistent with this interpretation, including this interaction in the regression model explained additional variance (see Figure 12). However, this increase was not statistically significant.

The simplest explanation as to why I did not observe bigger effects for the momentum manipulation is that I did not use heavy enough masses. The more likely possibility is that the way I presented the tasks to participants did not allow for clear discriminations of mass differences. Future research can address the latter possibility by asking participants to choose between an object that is loaded and one that is unloaded. Other opportunities for future research are discussed next.

Future Research, Additional Caveats, and Concluding Remarks

As argued above, the task-choice method seems flexible enough to address more empirical questions in future research. In addition to presenting participants with the opportunity to choose tasks with different loads, it would be interesting to know whether different patterns of choices would be observed when the other factors are presented in different ways. For example, the speed sensitivities I observed may have been even more dramatic if the tasks were presented in a way that makes the speed differences more salient. One way to investigate this possibility would be to present a different driving period for each task as opposed to presenting both tasks in the presence of the same driving period as I did here. Such investigations may be particularly useful for teasing apart the specific relations between the perceptual features of the tasks and the actions they afford. Recent research has provided evidence that perceptual discriminations are grounded in the perceiver's ability to act on those perceived dimensions (for a review of this literature, see Proffitt, 2006).

Two additional caveats need to be addressed. First, the regression models do not serve as models of the choices that participants made on any given trial. Raising this caution is necessary because the models estimated the effects of each factor on the pooled likelihood that each alternative task was chosen, irrespective of the constant task with which the alternative was paired. As a result, the models only estimated the effect that each factor had on the overall popularity of the alternative tasks.

A related caveat is that the analyses used here make it difficult to determine whether task popularity was influenced by previous choices. While it is clear that hysteresis effects exist in motor control experiments (Zhang & Rosenbaum, 2008), the fact that the current data were pooled across groups makes it hard to know whether any given choice was influenced by previous decisions. However, it should be noted that the present study controlled for these effects by randomizing the order of the trials and driving period blocks (see Method). This randomization helped ensure that sequence effects could not explain task popularity across participants. Future research might address this issue directly by including specific orders of task presentations as between-subject variables.

In summary, I extended the task-choice method to estimate the movement costs of a number of task factors. The current study provides evidence that movement speed, hand-use, and leaning all contribute to effort. The primary value of these findings lies in the confirmation that the task-choice method can be used to estimate the relative costs of interacting with specific task dimensions. Moreover, the task-choice method appears reliable and flexible enough to be address questions about the relative importance of each factor during planning. The method should therefore be useful for evaluation of movement planning theories that assume these costs are taken into account. Without an independent cost measure, these theories are, strictly speaking, circular (Rosenbaum & Gaydos, 2008). For example, the finding that participants placed a high priority on minimizing the cost of translocation distance with respect to time is in good agreement with the posture-based motion planning theory, which relies on task-specific minimization of travel costs in order to specify goal postures and movement times for reaching actions (Rosenbaum et al, 2001). Furthermore, this model of motion planning holds that one of the most important aspects of motion planning is establishing a constraint hierarchy, which is a set of prioritized requirements defining the task to be performed. The foregoing results suggest that the minimization of speed is a high constraint.

It remains necessary to understand how effort is generally represented. To this end, I would like to suggest that the task-choice method need not be limited to the estimation of movement costs per se. Rather, future research can also explore the method's ability to quantify effort across qualitatively different tasks. For example, one could ask participants to choose between a cognitively demanding task like mental arithmetic and a physically demanding task like running on a treadmill. Regardless of the particular tasks researchers choose, an investigation like the one just suggested should be useful for defining effort across domain-specific tasks. The task-choice method used here puts that goal within reach.

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