# Abstract (150 words)

A decision-making framework suggests that the goal of a movement is to maximize utility, represented by the sum of the reward and effort associated with a movement [1]. Reward has been shown to increase movement vigor, but it is unclear how effort affects movement vigor [2]. With two experiments, we examine how effort (i.e. mass) affects metabolic cost and self-selected movement speeds. We then compare a utility model, with effort as metabolic cost, to the self-selected movement durations. The metabolic power of the movement was increased by both mass (p = 2.52e-7) and speed (p < 2e-16). The increase in metabolic cost due to increasing mass was found to be sublinear (m0.83). We find that mass increased movement duration (p < 2e-16), decreased peak reaching speed (p < 2e-16), and increased reaction time (p < 2e-16). We find that metabolic cost alone cannot predict the preferred movement duration, but a utility model can.

# Introduction (Total Paper < 5000 words, excl. Methods & References)

The speed of our movements is influenced by both the expectation of the reward to be acquired and the effort to be expended. While there is a growing body of work demonstrating the effects of reward on invigorating movements across a range of movement descriptors (reaction time, movement time, movement distance) and their neural correlates, considerably less is understood regarding the effect of effort on movement vigor.

More effortful movements tend to be slower. Animals choose to walk slower when carrying heavy loads and when walking up inclines (Ref). Even at the level of reaching, we reach slower in directions that involve moving more mass [3], [4]. It is not entirely clear why we and other animals do this. Slowing the movement down will not necessarily cost you less energy overall, and it certainly will not save you time. So why do we tend to move slower when the movement becomes more effortful?

Scientists have often looked to metabolic energy costs in order to explain the choice of movement speed. The total metabolic energy expenditure to walk or run a fixed distance, also called the cost of transport (COT), exhibit U-shaped curves with movement speed [5]–[7]. The minima indicate the metabolically optimal gait speed, i.e., the speed that minimizes the total metabolic cost in joules to move a fixed distance. When allowed to freely select their gait speed, humans often choose walking and running speeds that approximately coincide with the metabolically optimal speeds [6]–[8]. This has also been shown in a number of animals and gaits [9], [10]. One study had horses walk on a treadmill inclined at various levels and measured cost of transport as well as the horses’ preferred walking speed [11]. Cost of transport increased with incline, and the metabolically optimal speed decreased. The horses’ preferred walking speed slowed down at greater inclines and intriguingly, generally tracked the metabolically optimal speed.

These results would suggest that metabolic cost per unit distance uniquely determines preferred movement speed and that the slower movements indicate that the metabolically optimal speed has shifted. Beyond the fact that the data are rather sparse, there are a few more issues with this conclusion. First, the metabolically optimal speed does not always shift with increasing mass [12]. Despite this, humans walk slower with greater loads [13]. Thus, it appears that minimizing metabolic cost of transport is not the sole factor determining movement speed. Secondly, there is a wealth of data demonstrating that animals move faster towards more rewarding targets [14], as well as even faster to the same target but in more rewarding environments (Ref). Moving faster alters the movement’s cost of transport, potentially shifting it away from the metabolically optimal speed. By doing so, are animals sacrificing optimality or are they optimizing for a different currency of value, utility, that not only considers the metabolic cost of the movement but the reward to be acquired as well? Support for the latter can be found in the behavioral ecology literature on optimal foraging theory [15], [16]. A movement utility that has been quite successful in explaining animal behavior is one based on the maximization of capture rate, where capture rate is the net gain (metabolic rewards minus metabolic costs) divided by time [1]. Thirdly, recent results suggest that humans do not represent effort as metabolic cost, but rather as a nonlinear, quadratic mapping of it. Taken together, it isn’t clear whether the effort-related slowing is due to optimization of a utility that 1) consists solely of metabolic cost of transport, 2) considers both reward and effort, or 3) considers a representation of effort other than metabolic cost?

Here we approached the question of how effort determines movement speed from a neuroeconomics perspective. We quantified an objective measure of effort and then determined which representation of economic utility best explained measured reductions in preferred movement speed with increasing effort. Specifically, we measured the metabolic cost of reaching with added mass, obtaining an objective measure of reaching effort. Metabolic cost increased with mass and exhibited near-linear increases with greater mass. Next, we measured the effect of added mass on the choice of movement speed and observed that movement speed decreased with added mass. Lastly, we asked to what extent this reduction in vigor could be explained by metabolic cost. Ultimately, the choice of movement speed was best explained with the maximization of a utility that considered both the reward at stake and the effort to be expended, where effort was represented objectively as metabolic cost. In contrast, a utility that did not consider reward and consisted solely of metabolic cost, and a utility where effort increased quadratically with metabolic cost, were less successful in accounting for movement choices. These findings demonstrate that metabolic cost, while necessary, is not sufficient in determining preferred movement speed.

# Results

While it is often observed that increased effort will lead to slower movement, it is unclear exactly why this occurs. Part of the problem is that without an objective measure of effort we are left unable to quantitatively describe the effects of effort on the selection of movement speed. Therefore, in the present study, our first step towards understanding the effect of effort on movement speed was to quantify an objective measure of increasing effort. To do so, we measured the metabolic cost of reaching with increasing effort where effort was modulated by increasing the mass at the hand.

## Study 1 - The effect of mass on the metabolic cost of reaching

Healthy, young participants (N = 8) made 10cm reaching movements at six prescribed speeds with four different masses (0kg, 2.3kg, 4.5kg, and 9.1kg) added at the hand for a total of 24 sets of reaching conditions (Fig. 1). Conditions were blocked with each consisting of ~200 trials. As they performed the task, we measured metabolic rate via expired gas analysis. Metabolic rate is calculated from the last three minutes of reaching within each block of reaching movements.

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| Figure 1 Caption –  Experiment 1 setup. (A) Subjects made horizontal planar reaching movements on a Shoulder-Elbow Robot from Interactive Motion Technologies. Oxygen consumption rate and carbon dioxide production rate was collected using a Parvomedics metabolic cart. Inertial mass was added at the hand. (B) Subjects made reaching movements across a range of added masses and speeds to four targets. There were seven distinct speeds, and subjects completed six speeds with each mass. The two heaviest masses corresponded with the six slowest speeds; the two lighter masses corresponded with the six faster speeds. The number of trials within each speed was set to allow for approximately five minutes of reaching. |

### Metabolic expenditure increases with mass

Before participants performed the reaching task, we measured their resting metabolic rate, in three five-minute baseline periods, as they sat quietly in the experimental chair. On average, the resting metabolic rate was = 73.33 ± 3.6W. As they performed the reaching task, gross metabolic rate increased with faster reaching speeds (Est = -7.67e-1, p < 2e-16). With no added mass, gross metabolic rate ranged from 92.78 ± 6.63W for the slowest reach to 171.98 ± 18.51W for the fastest reach. Furthermore, across movement speeds, gross metabolic power increased significantly with added mass (Est = 1.73e-2, p = 2.52e-7; Fig. 2A). For a movement of a similar speed, adding 9.1kg of mass at the hand led to an increase in gross metabolic rate from 131.65 ± 14.32W to 222.06 ± 24.39W, a nearly 70% increase. Thus, faster reaches with greater mass led to increased metabolic rate.

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| Figure 2  Experiment one results. (A) Gross metabolic power is increases with effective mass of the arm. Mass does not scale in a linear manner however, and scales sublinearly with mass (i = 0.83). This also shows that as the movement gets faster, gross metabolic power increases very quickly (j = 5.82). We also see that the horizontal asymptote of gross metabolic power is also higher than the gross metabolic resting rate (a = 98.25, resting = 73). (B) Multiplying gross metabolic rate by movement duration we can estimate the gross metabolic cost of a movement. We see that gross metabolic cost shows a distinct minimum, and that this minimum duration increases with added mass. (C) Mass and speed (reduced duration) increased subjects endpoint error. (D, E) Another metric of accuracy, consistency of the movement, shows that mass did not affect subjects’ movement consistency. Faster movement speed did lead to less consistency (increased variance). (F) Although the phase before reaction time subjects are not moving, we see that increased mass and increased movement duration led to increased reaction time. |

We next sought to quantify how metabolic rate scaled with mass and movement duration. We parameterized metabolic rate as a function of mass and movement duration by fitting the gross metabolic rate data to the following equation based upon the observed effects of mass on the metabolic cost of walking:

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|  |  | (1) |

where represents the effective mass of the arm with the added mass (see Methods), and is the movement duration. The best fit parameters were , , , and (SSE = 120872.75, AIC = 1750.83). We tested an alternative formulation wherein the constant, a, was also scaled by the effective mass of the movement raised to a power:

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This fitted value for k was not different from zero and the model performed similarly compared to Eq. (1) (k = -0.02 +/- 0.04, ­SSE = 120743.07, AIC = 1752.63), indicating that the time-invariant component of metabolic power did not change with added mass. Thus, we moved forward with Equation 1.

Equation (1) represents the average rate of gross metabolic energy expenditure (joules/s), over the course of a reach of a given duration and mass. To obtain the total gross metabolic cost of that reach in joules, , Eq. (1) is multiplied by the movement duration:

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The metabolic cost of a very fast reach is quite high, reduces as the movement slows down, but then increases again at slower speeds (Fig. 2B). The minimum of this curve represents the movement duration that would minimize the metabolic cost of the reach, i.e. the duration that minimizes cost of transport. From Fig. 2B, we can see that this duration increases with added mass. We will return to this finding later.



### The effect of mass on movement accuracy

Another aspect of movement that is affected by the speed of the movement is accuracy, i.e. the speed-accuracy tradeoff. We measured accuracy as the Euclidean endpoint error at movement offset (see Methods). As expected, endpoint error was reduced with longer movement durations (Est = -9.37e-1, p < 2e-16). We also asked the analogous question of whether mass affects movement accuracy. Indeed, we found that mass slightly increased endpoint error (Est = 2.16e-2, p < 2e-16), with the strongest effects seen at the fastest speeds (Fig. 2C).

Accuracy can also be reflected in the consistency of the movement, defined as the variability in endpoint position, independent of the actual target error. We split consistency into two metrics, angular endpoint variability and radial endpoint variability. Radial endpoint is how far from the home circle participants ended their movement, and angular endpoint is the angle between the target vector and endpoint vector measured from the home circle. Both radial and angular variability decreased with movement duration (Est = -1.00, p < 2e-16, Est = -1.14, p < 2e-16), while mass did not affect either (Est = -6.92e-3, p = 0.287, Est = 1.74e-2, p = 0.0114, respectively; Fig. 2E).

### Slower reaction times with added mass

An interesting question is how effort affects reaction time. While we enforced the duration with which subjects had to complete a reach, participants were free to select the combination of reaction time and movement duration. The choice of reaction time has been related to the process of planning the upcoming movement, suggesting that the predictable mass in this experiment should have little effect. Moreover, one might predict that reaction time should not be affected by mass because participants are not moving while preparing the action. Here we found that reaction time increased with mass (Est = 2.40e-3, p = <2e-16) and movement duration (Est = 6.43e-2, p < 2e-16; Fig. 2F). Thus, slower movements had longer reaction times, and for two movements of the same duration, the movement with the greater mass elicited a longer reaction time.

To summarize the results of Experiment 1, we found that it is more energetically costly to make reaching movements with greater mass. This increase in metabolic cost is not proportional to the increase in mass, but rather diminishes with additional mass. Mass also led to an unexpected increase in reaction times, with participants reacting slower with added mass, even though the subsequent movements were of the same duration.

## Study 2 - The effect of mass on preferred reach duration

Given that mass leads to an increase in the metabolic power of reaching, how will this increased effort cost influence an individual's preferred movement speed? The second study was designed to answer this question. Similar to the previous experiment, participants made goal-directed reaching movements with added mass at the hand (Fig. 3). However, rather than reaching at a prescribed speed, participants were free to reach at a self-selected speed. At the beginning of each trial, one of four targets would appear centered on the circumference of a 10cm circle and participants were asked to reach to the target to complete the trial. To control for any confounding effects of accuracy on mass-related changes in preferred movement speed, three separate experiments were run each with a different target size or stopping requirement. In Experiment 2a, the target configuration was identical to Experiment 1 and participants were required to stop in the target. In Experiment 2b, accuracy requirements were increased. The target size was reduced to a thin, narrow arc, where again participants were required to come to a stop. In the third experiment, Experiment 2c, accuracy requirements were reduced to nearly nothing and target stopping requirements were removed altogether. Participants had to make an out and back movement in the direction of the target where the only requirement was to cross the outer 10cm circle, in the quadrant of the indicated target. All experiments consisted of 1600 total trial in the added mass conditions, divided into four sets of 400 trials each. In each set of 400 trials, a different mass would be added to the robot handle. The amount of added mass was hidden from the participant using an opaque container and could be 0kg, 1.36kg (3lbs), 2.27kg (5lbs) or 3.63kg (8lbs) (Fig. 3). All participants experienced each mass condition once, and the order was randomized across participants.

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| Figure 3  Experiment 2 protocol. Subjects underwent five blocks of reaching movements including a familiarization block and four added mass blocks. The order of mass conditions were randomized for each subject. The setup and subject position are the same as experiment 1. (A) Experiment 2a block setup. Subjects completed 400 trials in familiarization and each mass condition. Subjects made reaching movements from a home circle and stopped at one of four targets, 10 cm away from the home circle. The target and home circle would switch positions, and subjects would complete another movement back towards the center of the screen. (B) Experiment 2b block setup. Subjects complete 400 trials of familiarization and 200 trials for each added mass condition. Subjects would make 10 cm reaching movements from a home circle to a small arc shaped target. After stopping at the target, subjects would move back towards the home circle. (C) Experiment 2c block setup. Subjects complete 100 familiarization trials, and 200 out and back reaching movements for each mass. Subjects started in a home circle, and reached in one of four directions with the only criteria that they move at least 10 cm. After moving at least 10 cm, subjects would reach back towards the home circle. |



### Mass led to slower movements

In each of the three experiments, added mass led participants to make significantly slower movements. This is reflected in significantly longer movement durations and lower peak velocities across the three experiments (Movement Duration: Est = 3.76e-2, p < 2e-16, Peak Velocity: Est = -1.61e-2, p < 2e-16; Fig. 4 D, E, F).

We also found that in each of these experiments, the change in movement duration due to mass was relatively the same (Fig. 4G). We fit an individual linear mixed effects model predicting the effect of mass on movement duration for each experiment and compared the magnitude of the effect across experiments. All experiments showed a significant effect of mass, with similar slope estimates, suggesting that the effect of mass was conserved across experiments. This is further demonstrated in Figure 4G where the normalized movement durations (normalized to 0 added mass) are plotted. We see that across experiments, the changes in movement duration with added mass were relatively similar.



As expected, we observed an effect of an experiment's accuracy requirements on the preferred movement duration. Experiment 2b, with the smallest target exhibited the longest movement durations and lowest peak velocities. Experiment 2c, which had no stopping requirements, led to the shortest movement durations and highest peak velocities (Fig. 4 D, E). Thus, even when accuracy costs are negligible, mass leads to a significant increase in movement duration and reduction in speed. This suggests that mass-related reductions in accuracy are not driving these changes in selected movement speed.

### Mass Increased Reaction Time

Like to experiment 1, we investigated how mass affected reaction time. One might predict that reaction time should not be affected by mass because subjects are not moving while preparing the movement. In these experiments, subjects were free to choose both movement duration and reaction time with no restrictions. Across all three experiments, mass increased reaction time (Est = 5.461e-3, p < 2e-16; Fig. 4G). The average reaction times in experiment 2a, for 0, 3, 5, and 8 lbs, were 0.180s, 0.186s, 0.189s, and 0.197s respectively. We found that increasing mass increased reaction time in all three experiments (2a Est = 4.645e-3, p < 2e-16; 2b Est = 5.313e-3, p < 2e-16; 2c Est = 6.401e-3, p < 2e-16; Fig. 4F). The effect of mass is conserved across experiments as seen in the linear estimates and in Fig. 4I. These results from experiment two solidify the finding that mass increases reaction time.

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| Figure 4  Experiment 2 results.  Average velocity traces shown for experiment 2a (A), experiment 2b (B), and experiment 2c (C). Each line represents the average for one mass condition, with the peak velocity indicated by a dot. We see that added mass reduced peak velocity, also causing the peak velocity to occur later in the movement. In panel D-I, each point represents the average of the subjects’ average for a specific mass condition. Error bars show standard error across subject averages. Horizontal dashed lines show the average value for 2.47 kg of effective mass. (D) Mass increased movement duration across all three experiments, reciprocal to movement duration, (E) mass reduced peak velocity across all three experiments. (F) Reaction time was increased by increased mass across all three experiments. (G) Movement duration, (H) peak velocity, and (I) reaction time were affected by mass in a similar manner across all three variations of experiment 2. |

### Mass may affect endpoint error

Did the added mass also influence characteristics of how the movement ended? Experiment 2a and 2b had imposed stopping requirements, described in detail in the methods. Experiment 2c had no stopping requirement. Rather, participants were asked to make a shooting movement through the target and return to the home circle. Thus, as a measure of endpoint behavior we looked at the maximum excursion of their movements, taken as the point at which they turned around to return to the home circle. For experiments 2b and 2c, we found that mass did have an effect on endpoint error (2b Est = -1.389e-4, p = 0.879e-5; 2c Est = 1.023e-3, p < 2e-16), though in opposite directions. Experiment 2a did not show an effect of mass (Est = -3.925e-5, p = 0.149).

We also investigated subjects’ consistency and how it was affected by mass. Radial endpoint variability was not affected by mass in any of experiment 2 (2a Est = -4.307e-3, p = 0.275; 2b Est = -4.993e-3, p = 0.080; 2c Est = 0.258, p = 3.343e-3). Angular endpoint variability was not affected by mass in any of experiment 2 (2a Est = 0.090, p = 0.233; 2b Est = 0.407, p = 0.526; 2c Est = 0.678, p = 0.750).

In summary, added mass led to a slowing of preferred movement speeds. Increasing accuracy requirements also led to general movement slowing, however the effects of mass were conserved, and mass consistently led to reductions in movement speed independent of the task’s accuracy requirement.

## Movement Utility

In Experiment 1, we observed that mass increases the effort cost of movement. In Experiment 2 we saw that mass also increases preferred movement durations. Can we explain these effort-based changes in movement preference in the context of a movement utility that is conserved across individuals? To investigate this question, we turned to the literature on optimal foraging theory, wherein animal behavior is theorized to agree with the goal of maximizing capture rate, maximizing the net gains (rewards minus costs) per unit time. If we assume that the purpose of movement is to acquire reward as quickly as possible but with minimal effort, we can represent the utility of movements, J, similarly as a capture rate:

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Here  is the reward to be obtained,  is the cost of obtaining the reward, and  is the total time spent acquiring the reward. In the context of movement, the primary cost is effort, and we can represent the movement effort cost as the measured metabolic cost of a reach of a given mass and duration, . However, there is also the time spent preparing the movement, i.e. the reaction time. The effort cost associated with reaction time, , is equal to the metabolic expenditure when not reaching, represented as  multiplied by the reaction time, , in Eq (1). The total time to reward, , then is the sum of the reaction time and movement duration. This leads to the following expression for a utility reflecting the capture rate where effort is represented as metabolic cost:

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We have included the term, , to reflect the probability of reward and its dependence on the duration of the movement, i.e. the speed-accuracy tradeoff and mass. We used a logistic function fit to endpoint accuracy data from experiment 1 to capture the relationship between movement duration, mass, and the probability of ending the movement within a target of a given size:

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Since experiments 2a and 2b had targets of different sizes, a separate function was fit for each experiment, yielding two sets of parameters and resulting curves reflecting the greater accuracy requirements enforced in Experiment 2b (Experiment 2a: ; Experiment 2b:; Fig. 5B). As there were negligible accuracy requirements in Experiment 2c, was set to 1.

At this point, for a given reward, , we can calculate the optimal movement duration, , that will maximize the capture rate, . To determine whether maximization of movement utility can explain the changes in preferred movement speeds seen in Experiment 2, we used numerical optimization to fit  that minimizes the error between experimental data and predicted optimal durations. A single  was fit to the combined data from Experiments 2a and 2b across all mass conditions, as the experiment specific speed-accuracy curves accounted for the sole difference between the experiments. With only a single parameter to fit, across all mass conditions and two target sizes, we find that net capture rate can describe preferred movement durations rather well ( , SSE = 5.24e-3). If we fit  to each experiment individually, we see that the values are not very different with  values of 59.34 and 105.78, and corresponding SSEs of 1.49e-4 and 1.08e-3 for Experiment 2a and 2b respectively (Fig. S1). A separate  was fit to Experiment 2c, since the movements were qualitatively different (i.e. out and back vs out and stop). For Experiment 2c, the predicted optimal durations also match those observed (, SSE = 9.69e-4). The total SSE across all three experiments was 6.20e-3.



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| Figure 5 Caption Model Fits for all experiments  (A) Using the data from experiment 1, and the logistic regression shown in Eq. 5, we can compute the probability of success given the criteria for experiment 2a and 2b. Data points are the fraction of trails within that condition that were a success. The regression for experiment 2a criteria is shown with a solid line and circle data points. The regression for 2b criteria is shown with a dashed line and square data points. We see that the probability function can well represent the data seen in experiment 1. Each line is colored by mass added from experiment 1.  (B) Using the regressions from Eq. 5, we can apply this to the masses and movement durations see in experiment 2. This plot shows how the regressions map onto the data seen in experiment 2a and 2b. As with panel A, experiment 2a is shown with a solid line and experiment 2b is shown with a dashed line. The fractional success is shown with vertical error bars. For experiment 2a, the regression slightly underpredicts the probability of success for a given movement duration. For experiment 2b, the regression slightly overpredicts the probability of success for a given movement duration.  (C) Utility fits by experiment. Each solid line with error bars (standard error across subjects’ average) represent the average movement duration for experiment 2a (pink), 2b (blue), 2c (green). The dashed lines indicate different optimal utility durations. For experiment 2a and 2b, we fit one α value (α = 68.137) to find the durations predicted by optimizing utility. We see the utility model does a reasonable job and predicting two experiments by altering the probability of task success (SSE = 5.24e-3). When fitting another α value (α = 95.665) to 2c, we find that utility can predict the movement durations (SSE = 9.69e-3). The black dashed line indicates using the α value from experiment 2a and 2b, setting the probability of success to 1, then finding the optimal durations. We see that it is not quite able to predict the movement durations seen in experiment 2c. The dashed red line indicates the gross metabolic minima duration. This shows that the metabolic minima lines up very well with experiment 2c (SSE = 1.972e-3). |



# Discussion

In this study we found that adding mass at the hand led subjects to make increased duration and reduced vigor reaching movements, and adding mass increased the metabolic cost of reaching in a sublinear manner. A recently proposed utility framework, that represents effort with metabolic cost discounted by time, can explain the movement duration across multiple experiments [1]. When comparing the metabolic cost minimum to the preferred reach duration of subjects, we find that minimizing metabolic cost alone cannot predict the preferred movement duration.

## Cost of Transport

One common method used to explain movement speed is to minimize the total metabolic cost of the movement. Minimizing metabolic cost of transport has been used to explain preferred walking and running velocity across many different studies [6]–[8], [17]–[24]. In this study however, we found that subjects typically do not make their reaching movements at the metabolic minimum. A possible explanation is that when making reaching movements effort is discounted by time. Temporal discounting has been shown in relation to rewards as well as cost of time [25]–[27]. The utility model presented here assumes that both reward (α) and effort (E) are both discounted by time [1]. When discounting both by time, either gross metabolic cost or net metabolic cost can explain the preferred reach duration. However, the type of metabolic cost that we use affects the α parameter that is fit in the utility framework (Eq. 5). Using gross metabolic cost, we find α = 68.137.

## Quadratic Representation

This leads researchers to minimizing a proxy for metabolic cost in many studies [28]–[33]. It is unclear though how these proxies for effort represent how humans chose reaching movement durations. A very common proxy, sum of torque squared, does a very poor job at predicting movement related kinematics (Fig. S1). Sum of torque2 does not match well with preferred movement duration. By fitting a similar model to the metabolic power models (Eq. 3), we can determine how sum of torque2 scales with added mass. We found that metabolic cost (and preferred movement duration) scales in a sublinear fashion according to the metabolic expenditure section and Eq. 4. Sum of torque2, however, increases in a super linear fashion with mass. Therefore, we see a large difference in the preferred durations and the duration that minimizing sum of torque2 would predict.

## Accuracy

Across both experiments, the effect of movement duration on endpoint error was much larger than the effect of mass. In experiment 1, subjects were forced to move in specific time windows which is may have caused the effect of mass in this experiment. Experiment 2 did not show an effect of mass but experiment 1 did. In experiment 2, subjects were free to choose their movement duration. Increasing movement duration reduced error as the speed accuracy trade-off would predict [34], [35]. Mass did not change the consistency with which subjects made their movements in either experiment, but as expected, movement duration reduced the endpoint variability. Angular error variability may be affected by mass (p = 0.0114), but this could be driven by the subjects preferring to reach more towards the lower inertial directions of the arm as the lowest inertial directions are not oriented exactly at 45o and 225o, which caused subjects to reach slightly off center from the target [3].

## Reaction Time

We found that increasing the effort of a movement also increases the reaction time and this can be predicted by the utility model [1], [2]. It has been shown that increasing reward leads to early reaction times by increasing the total utility of the following movement. The opposite is also true, where increasing effort reduces utility and leads to longer reaction times. The rate of evidence may be linked to the utility being assigned to the movement [1]. This leads to lower utility movements having a lower evidence accumulation rate which leads to longer reaction times. Drift diffusion models have been shown to make accurate predictions of reaction time [36], [37]. In this paradigm subjects react once evidence for a movement has accumulated to a certain threshold. In our study all the targets were the same shape within an experiment, so rate of evidence accumulation may be the same. Knowing this, our result that subjects reacted slower may indicate that more evidence was required before movement initiation for higher effort movements.

In this study we wanted to determine the effect of mass on the movement duration of reaching movements, and if we can use metabolic cost or utility to explain these movement durations. We found that adding mass (effort) to a movement increased the movement duration. Minimizing the metabolic cost of the movement was not able to predict these movement durations, but a utility framework is able to predict the movement duration of arm reaches.

# Methods

This study is composed of two main experiments (1 and 2), and a theoretical model. The first experiment is designed to determine the effect of mass and speed on the metabolic power of reaching and determine at what reaching speed the metabolic cost minimum occurs. The second experiment aimed to determine how mass affected the preferred reaching speed of subjects to compare to the metabolic minimum determined in experiment one. Two variations of experiment 2 were ran, with each altering some target parameters from experiment one. The last part of this study aimed to determine which utility can best explain the preferred reaching durations of subjects. All kinematic experiments were completed on a Shoulder-Elbow Robot from Interactive Motion Technologies.

## Experiment 1 - Effect of mass on metabolic power

In the first experiment, 5 male and 3 female, all right handed, with an average age of 28.9 years (std = 5.7), average weight 68.4 kg (std = 11.4), and average height 174.1 cm (std = 10.2) completed the metabolic protocol. Subjects completed reaching movements with varying speed and mass requirements while breathing into a Parvomedics metabolic system to collect metabolic data as a function of mass and speed (Fig. 1A). The seat subjects sat in was height adjusted to place the screen was place ~3 feet in front and 1 foot above of the subjects’ eyeline, with their arm in a horizontal planar position. All subjects reported no neurological, cardiovascular, or biomechanical problems that could interfere with the study. Subjects would complete the experiment in two sessions, where each session consisted of two sets of the mass conditions at the prescribed speeds. One subject completed the protocol over 3 sessions. All participants reported no neurological, cardiovascular, or biomechanical problems that could interfere with the study. Subjects gave written informed consent that was approved by the University of Colorado Institutional Review Board.

### Kinematic Data Collection

Subjects were trained to move a cursor from a home circle and stop at a target circle within a specified time window with breathing into a Parvomedics metabolic cart. Subjects made reaching movements in seven distinct time windows across four different masses (Fig. 1B). A block refers to one speed combined with one mass condition. The number of trials per block were calculated for five minutes of reaching at the desired speed, where the first 20 trials of each block were used for training. To begin a trial subjects held a circular cursor (r = 0.4 cm, yellow colored) within the home circle (r = 1.1 cm, white circle) location for 200 ms. The home circle then disappeared and a target circle (shape dependent on experiment) 10 cm away appeared randomly at 45, 135, 225, and 315 degrees from the right horizontal. In training, a blue dot would make a simulated movement from the home circle to the target circle using a minimum jerk trajectory. Feedback on movement duration was given when the center of the cursor was within the target the first time. If subjects moved too slow the target circle would turn grey, whereas if the subject moved to quickly the target would turn green. Making the movement within the time window caused the target to explode and turn yellow and play an auditory tone. Once completing an outward reaching trial, the home and target circle would swap locations and the subject would make another reaching movement towards the center of the screen. A subject would go out and back to each of the four outwards directions in a pseudorandom order then begin again. Subjects completed four different mass conditions and six different speeds. The completed mass conditions were 0, 5, 10, and 20 lbs of added mass at the robot handle which supported the vertical mass. The seven different time windows were: Very Slow (VS, 1.25 – 1.35 s, 160 trials), Slow (S, 1.05 – 1.15, 170 trials), Medium (M, 0.85-0.95 s, 200 trials), Fast (F, 0.65-0.75 s, 220 trials), Very Fast (VF, 0.45-0.55 s, 240 trials), Very, Very Fast (VVF, 0.325-0.425 s, 250 trials), and Very, Very, Very Fast (VVVF, 0.225-0.275 s, 260 trials). For 0 lbs and 5 lbs added, subjects would complete the speed conditions of S to VVVF. For 10 and 20 lbs added, subjects would complete the speed conditions of VS to VVF. The added weight only influenced the inertial properties of the arm in the horizontal plane.

### Metabolic Data Collection

Participants made arm reaching movements for five minutes in each block while collecting metabolic data approximately every 5 seconds using a Parvomedics metabolic cart system. Subjects wore a nose clip and breathed through a short tube into the Parvomedics system. The cart measured consumption and production. Participants were required to be well rested and have fasted for 8 hours before testing. Testing sessions began with the participant resting in a seated position in a chair for 10 minutes while the system was calibrated using a 3L syringe. Three baseline readings were then taken for 5 minutes each before the experimental protocol began. Participants then began the arm reaching trials. Five minute rest periods were provided between each block of reaching trials.

## Experiment 2 - Effect of mass on preferred movement duration

In the second experiment, a separate cohort made seated horizontal arm reaching movements using a robotic arm manipulandum (Interactive Motion Technologies Shoulder-Elbow Robot 2) while secured to a chair by a 4-point seat belt. The seat was height-adjusted to place the screen ~3 feet in front and 1 foot above the participant’s plane of view, with their arm in a horizontal planar position. All participants reported no neurological, cardiovascular, or biomechanical problems that could interfere with the study and gave written informed consent that was approved by the University of Colorado Institutional Review Board.

### Kinematic Data Collection

Subjects made reaching movements within five blocks. The five blocks were a familiarization block, 0 lbs, 3 lbs, 5 lbs, and 8 lbs added at the hand. The order of the weighted conditions was randomized for each subject. The downward weight of the added masses was supported by the robot so these masses only added inertial effects to the arm. The position of the handle controlled a cursor on a computer screen that was placed just above head level and about 3 feet in front of the subject. Subjects arm positions started in approximately the same orientation. Visual feedback was provided to the subjects throughout the experiment on whether they completed the reach movement in the prescribed duration. To begin a trial subjects held a circular cursor (r = 0.4 cm, yellow colored) within the home circle (r = 1.1 cm, white circle) location for 200 ms. The home circle then disappeared and a target circle (shape dependent on experiment) 10 cm away appeared randomly at 45, 135, 225, and 315 degrees from the right horizontal. A subject would go through all four outward targets in a pseudorandom order then begin again.

#### Experiment 2a

In this experiment 9 male and 3 female subjects, all right handed, with an average age of 25 years (std = 3.84), average weight 68.6 kg (std = 4.1), and an average height of 154.6 cm (std = 28.7) completed the experiment (Fig. 3B). Subjects underwent 5 different blocks of 400 reaching movements (200 out and back movements) to four different targets. The subjects would make horizontal arm reaching movements towards a circular target, similar to experiment 1 (r = 1.4 cm, red color). For each reaching movement, the target would explode indicating a correct movement duration as the movement duration criteria was set between 1ms and 10000 ms, so there were not time requirements imposed on the reaching movements. In this experiment we wanted to ensure subjects came to a complete stop before the trial ended, so the dot would explode after the subject had remained in the target for 300 ms and the velocity during that time was under 0.5 mm/s.

#### Experiment 2b

We wanted to ensure that the effects on movement duration from mass were not influenced by the size of the target or accuracy costs. We ran two more similar experiments in which we altered the shape of the target to change the accuracy costs of the movement.

In experiment 2b, there were 8 male and 4 female subjects who completed the protocol, with an average age of 25.3 years, average height of 68.6 inches, and an average weight of 154.6 lbs. Subjects completed 400 out and stop trials in familiarization, and 200 out and stop for each added mass condition. In this experiment, the target was a section of a 10 cm circular arc centered on the home circle oriented at the same positions as experiment 1 and 2a. Subjects would need to stop between 10 cm and 11 cm from the home circle and within 7 degrees of the center of the arc target for the target arc to turn green. If subjects overshot the target (went past 11 cm) the target would turn red indicating an overshoot.

#### Experiment 2c

Experiment 2c was completed by 18 subjects, 9 male and 9 female, with an average age of 25.1 ± 3.7 years old. Subjects completed 100 out and back movements for familiarization, and 200 out and back movements for each mass condition. The target was a 90 degree section of a circle that subjects had to reach towards. However, subjects did not need to stop at any specific location, just hit the target arc, turn around and return to the home circle. In this experiment we used the point that they turned around as the end of their movement. This experiment was used to simulate a zero-accuracy cost with a very very large target.

### Data Processing

Movement kinematic data was extracted and analyzed in MATLAB 2019a. X and Y positional kinematic data was collected at 200 Hz, then differentiated using a double five point differentiation and Butterworth filter (sampling frequency 200 Hz, cutoff frequency 10 Hz) to determine velocity and accelerations in the X and Y direction. We then compute the magnitude of the velocity and acceleration vectors.

#### Metabolic Processing

The gross metabolic rate was calculated in joules per second, , using the method described by Brockway (Eq. (7)) [38]:

|  |  |  |
| --- | --- | --- |
|  |  | (7) |

Baseline metabolic rate was subtracted from gross metabolic rate to determine the metabolic rate associated with the reaching movement only, or net metabolic rate. Subjects made reaching movements for 5 total minutes, but metabolic rate was calculated only using the last 5 minutes of each block to allow subjects to reach a steady metabolic rate while reaching. After data was collected, custom MATLAB scripts were used to parse the data by trial, mass, and speed. Movement duration was calculated using the last 3 minutes of trials within a block. The overall metabolic rate is then normalized by the fraction of time spent moving.

#### Movement Onset and Offset

Many of our metrics are dependent on identifying the instant the movement began (movement onset) and the instant the movement ended (movement offset). To detect movement onset and offset we used a custom algorithm for all experiments. Many reaction time algorithms are dependent on movement duration and we wanted to minimize this effect [39], [40]. We first compute the velocity towards the target by differentiating the distance from the center of the target. For movement onset we find the first time the velocity towards the target reached 20% of the maximum velocity towards the target. From there the algorithm searches backwards (in time) to a point where either there is either 4 frames of acceleration away from the target in the next 10 frames or where the standard deviation in the velocity towards the target was less than 2e-3 in those 10 frames. Using this method, we detect the first time the subject begins consistently accelerating towards the target. This led to detecting movement onset much earlier than many velocity thresholding algorithms, where we find an average velocity at reaction of -0.389 8.019for experiment one (mean sd), 1.019 2.220 mm/s in experiment 2a, -0.052 5.552 m/s for experiment 2b, and -0.098 5.077 mm/s in experiment 2c. To detect movement offset we found the first time the reaching movement was first 9 cm away from the home circle, then used the same method as reaction time to determine the offset. We find the first time the standard deviation of the velocity towards the target is less than 2e-3.

Because reaction time algorithms can be dependent on movement duration [39], [40], we needed to compare these changes in reaction time to computed reaction times from simulated movements. These movements can be generated using the range of movement durations in experiment 1 or 2 (methods, sec \ref{sec:get\_mvttimes}). This will inform us if the reaction time changes are due to changes in movement duration or added mass. We simulate reaching movements with similar movement times to the experiment using a minimum jerk trajectory and a simulation of the arm making reaching movements [30]. Using the minimum jerk simulation, we found that over the span of movement durations for experiment 1 the reaction time would increase with increasing movement duration. Over the movement duration ranges (.45 s – 1.4 s) the reaction time would increase due to the algorithm by 40 ms. Simulating the minimum jerk for experiment two, over the movement durations (0.77s – 0.90s), the reaction time would increase by 0.3 ms. We also used a biomechanical model of the arm like other studies to test if the change in reaction time could be attributed to subjects using the same control signal for different masses[41]. The reaction time change given the same control signal across masses was small, about 3 ms. In experiment one, the average reaction times across speeds ranged from 0.1377s to 0.245s. This is much larger than the effect of movement duration from the simulated movement durations simulation like experiment one (108 ms experimental vs 40 ms simulated). The algorithm used is affected by movement duration, but the change in calculated reaction time is greater than the range from just the effect of speed on the calculated duration.

In experiment 2, the range of reaction times calculated from the simulated movements ranged 0.3ms. The reaction times calculated from this experiment ranged by ~17 ms for experiment 2a, ~24ms in experiment 2b, and ~15 ms in 2c. The reaction time range in experiment one has a much larger range than the calculated reaction times of the simulated movements. This indicates that the changes in reaction time were due to mass, not the movement onset algorithm or changes in the movement durations.

#### Movement Duration

Movement duration is calculated as the time between movement onset and movement offset. The desired movement times in experiment one was generally longer than the prescribed movement times in the protocol. This is due to the feedback being given before the end the movement as subjects would take some time to settle on the target and feedback was given as soon as they touched the target. Movement duration was calculated using the time from reaction to the endpoint as described in the movement onset and offset sections, not the prescribed time windows.

#### Peak Velocity

We define peak velocity as the peak velocity towards the target in experiment 1, 2a, and 2b. Peak velocity towards the target is calculated by differentiating the Euclidean distance from the center of the target. Experiment 2c, as there really is no target, peak velocity is defined as peak outward velocity. Outward velocity is calculated by differentiating the Euclidean distance from the home circle.

#### Error Calculations

We investigated three measures of error for all experiments. Endpoint error was the Euclidean distance between the point at movement offset and the center of the target they were reaching towards. We then broke endpoint error into two consistency metrics, angular error and radial error. Angular error was calculated as the angle between the vector pointing from home circle to target circle, and the vector from home circle to where the subject ended the reaching movement. In this a clockwise angular error was considered negative. The second metric, radial error, was calculated as the Euclidean distance from the home circle at movement offset. Maximum excursion was also calculated as the greatest Euclidean distance from the home circle the subject reached during the movement. Experiment 2c had no stopping criteria, so endpoint error is defined as the maximum excursion.

#### Outlier Analysis

In experiment one, we removed outlier trials from the statistical analysis if they did not complete the movement correctly. Movement duration was calculated using all trials before removing any trials. We then removed any trial where the endpoint error was greater than 10 cm (reached the wrong target), the movement duration was less than 0.2 seconds or greater than 2 seconds (did not make the movement), the reaction time was greater than 0.50 s (failed to initiate movement), or the absolute miss angle is greater than 50 degrees (reached to wrong target).

For the kinematic statistical analysis, the data is then split into outward and inward reaching movements and we only use the outward reaches in the statistics. Inward and outward trials are split because on inward movements subjects knew where the target would show before it was indicated, which affects movement kinematics. After removal of trials, 27 out of 15925 outward trials were removed. Endpoint error, angular error variance, radial error variance, and reaction time are computed from the remaining trials.

In the second experiment, we removed trials that had movement durations 1.5x the interquartile range for each given mass. We did the same for reaction time and endpoint error. Reaches with a maximum excursion of more than 14cm were also filtered out in experiment 2a and 2b. The data from experiment 2a was also split into outward and inward trials for the same reason as experiment one. Statistics and kinematic analysis were done on the outward trials. This removed 702 out of 9600 outward trials in 2a; 671 trials of 9600 are filtered out for experiment 2b; 2335 of 14400 trials are filtered out for experiment 2c.

### Effective Mass Calculation

For all experiments the analysis uses effective mass of the arm as the mass term. Effective mass is an estimate of the arms resistance to a force in each direction[1]. Each subjects’ specific effective mass is calculated and used in the linear mixed effects models as described in in the statistical tests section. Average effective mass is used for plotting purposes. Segment lengths and masses are estimated from anthropomorphic measurement studies [42]–[44].

To determine the effective mass of the arm at a given time point we need to define a Jacobian matrix, . is the length of the upperarm and is the length of the forearm. and are the shoulder and elbow joint angle respectively.

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| --- | --- | --- |
|  |  | (8) |

The inertial matrix () is defined in Eq. (9), where mass is mass added at the hand. The centroid lengths, and , refer to the centroid length of the upperarm and forearm with mass added. and are the moment of inertia about the center of mass for the upper arm and forearm.

|  |  |  |
| --- | --- | --- |
|  |  | (9) |

The mass matrix is defined as:

|  |  |  |
| --- | --- | --- |
|  |  | (10) |

Last, we induce a force of 1 in the reach direction to compute the effective mass of the reaching movement. In Eq. (11), is the angle of reaching direction, and is added at the end to account for the inertia of the robotic arm manipulandum. We determine the effective mass of the arm in all four target directions, then average these to get an estimate for each individual subject.

|  |  |  |
| --- | --- | --- |
|  | Effective Mass = | (11) |

Each subject's specific effective mass was calculated using anthropomorphic measurements and estimates [42], [44], [45]. In the first experiment the effective mass of the four mass conditions were 2.44±0.064, 4.834±0.068, 7.127±0.070, and 11.691±0.071 kg. In experiment 2a the effective mass of the subjects and robot arm in these four mass conditions were about 2.508±0.074, 3.962±0.074, 4.890±0.075, and 6.271±0.077 kg.

### Modeling

This study has two primary modeling goals. First to model metabolic rate with an effort rate model, and second to determine how multiple cost models can predict preferred movement duration. In both the effort rate modeling and predicting the preferred durations, we use the group average data for effective masses, movement durations, and reaction times.

#### Effort Modeling

Effort modeling and parameter estimate were computed using the function nls from package nlstools. We define effort as the total cost to completing a movement, , and effort rate as the total cost per movement time, . Using the data in experiment one, we fit gross metabolic power, net metabolic power, and sum of torque squared to an effort rate model that parameterizes these variables as a function of mass and movement duration as seen in equation (12). The fitted parameters are . represents some offset from sitting while not reaching, is a scaling parameter, shows how effort scales with mass, and shows how effort scales with time.

Sum of torque squared was calculated using inverse dynamics of the arm reaches, squaring each time step, then integrating the torque over the duration. With sum of torque squared, we assume subjects attempt to minimize this effort representation. The durations that minimize sum of torque squared is then compared to the preferred movement durations.

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| --- | --- | --- |
|  |  | (12) |

Two additional effort rate models are fit to net and gross metabolic power data that include a term for either subject mass or effective mass that multiplies the parameter. These effort models are shown in equation (13) and equation (14). The added parameter in these models is . These effort models can be multiplied by time again to determine the cost associated with the movement.

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| --- | --- | --- |
|  |  | (13) |

|  |  |  |
| --- | --- | --- |
|  |  | (14) |

AIC and BIC scores are calculated for each effort rate model.

### Predicting preferred movement duration

To predict the average preferred movement durations we see form experiment 2, we created multiple potential models that should predict movement duration. We have two main models in this paper, metabolic cost (Eq. (15)) and utility (Eq. (19)). Metabolic cost and effort cost are computed by multiplying the previous effort rate models (Eq. (12), Eq. (13), Eq. (14)) by time, and we assume that subjects attempt to minimize this cost [7], [46]. Utility is determined by summing the rewards and efforts within a movement and temporally discounting both. Utility is then maximized to produce the preferred movement duration [1].

Predicting preferred movement duration with effort

Once a function for effort rate is determined we can multiply the function by time to determine the total effort cost of the arm reach (Eq. (15)). This is then used as an objective function to minimize when determining the movement duration that minimizes effort cost. When using effort cost to predict preferred movement duration, we assume that subjects would minimize this function and that this would predict movement durations.

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| --- | --- | --- |
|  |  | (15) |

Predicting preferred movement duration with utility

We also use a utility model to predict the preferred movement duration which assumes subjects will maximize the total utility of an arm reach. Utility is determined by the sum of the reward of the movement () minus the sum of the effort (), both discounted by time () and is shown in Eq. (16).

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| --- | --- | --- |
|  |  | (16) |

The utility model we use is slightly modified from other studies [1]. We use gross metabolic cost as the effort term in the proposed utility model (Eq. (17)), and can be seen in the metabolic cost fits (Eq. (15)). The new fitted parameter here is , which represents the reward associated with completing the arm reaching movement. Total time is split into reaction time and movement time. The reaction time of a movement is represented by , and represents the movement duration. The reaction times used from experiment 2a are 0.178 ± 0.013, 0.185 ± 0.014, 0.190 ± 0.013, 0.196 ± 0.013 for 2.47kg, 3.80 kg, 4.70 kg, 6.10 kg respectively. Experiment 2b reaction times were 0.205 ± 0.013, 0.215 ± 0.013, 0.219 ± 0.013, 0.229 ± 0.013. Experiment 2c reaction times were 0.199 ± 0.012, 0.208 ± 0.011, 0.213 ± 0.012, 0.216 ± 0.012. We scale by the probability of stopping within the target given the movement duration and mass. The full utility model is shown in equation (17).

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| --- | --- | --- |
|  |  | (17) |

The probability function scaling was determined using experiment 2a and 2b. The probability of success in experiment 2c was equal to one as there were no accuracy costs. Each movement in experiment 1 was labeled as a success according to the success criteria from experiment 2a and 2b. Thus, each trial in experiment 1 will have two labels for success. The first label from success in experiment 2a and the second from success in experiment 2b. For experiment 2a labeling, we labeled a reach as a success if the endpoint error was less than 1.4 cm. For experiment 2b, we labeled each reach as a success if the maximum excursion was less than 11 cm, and the angular error was less than 7 degrees. After determining if each reach was a success or not, we use an inverse logistic regression (R, glm model with binomial family and logit link function) to create the function for each experiment, shown in Fig. 5A and 5B. The probability function is shown in Eq. (18).

For experiment 2a, we found the beta coefficients of the regression to be for mass, for movement duration, and an intercept of . Experiment 2b had coefficients of for mass, for movement duration, and for an intercept. These logistic regressions represent in the utility model.

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| --- | --- | --- |
|  |  | (18) |

We optimize this utility model (Eq. (19)) by finding the value that minimizes the sum of squared error between predicted movement duration and the average movement duration from experiment 2a, 2b, and 2c. One value is fitted to each experiment, and then a single value is fit to experiment 2a and 2b together. This was done with the function optimize in R and a custom written error function.

|  |  |  |
| --- | --- | --- |
|  |  | (19) |

We fit multiple utility models to each experiment. We estimate the utility using gross metabolic cost, net metabolic cost, and sum of torque squared for experiment 2a, 2b, and 2c. Sum of squared errors are computed for each of the above utility models between predicted duration and duration seen in the experiment.

### Statistical Tests

Kinematic data was exported to R (v 1.2.5001) for statistical analysis. Linear mixed effects models were computed using the lme4 and multcomp package, and the functions used were lmer and cftest. To analyze the effect of mass on the kinematic variables we used linear mixed effects models. The effective mass used in the linear mixed effects models is the average effective mass for a human of 63.77 kg and 173.91cm tall with the added masses.

For experiment one, we tested a model with no between-subject variables and added mass and movement duration as within-subject variables. We tested gross metabolic power, endpoint error, endpoint angle variance, radial endpoint variance, and reaction time as dependent variables. Some variables were log-transformed to linearize the data for use in the linear mixed effects model. The outcome variables that were log transformed were metabolic power, the angle which subjects missed the target by (and variance), and subjects’ radial endpoint (and variance).

Lme4 log formula:

Lme4 non-log formula:

For experiment two we tested main effects of target, mass, and movement duration. Movement duration and velocity metrics only tested for main effects of mass and target.

Lme4 formula:

We use a significance level of or 2.5e-3 as we made 20 comparisons. Exact p-values are reported unless it is less than 2e-16. The linear model estimates are reported for the significant variables. For non-significant factors only the p-value is reported.

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# Supplemental

## Alternative models

**Metabolic cost:** A popular hypothesis in locomotion research is that humans and other animals choose the speed that minimizes the gross metabolic cost to move a fixed distance. We can test that hypothesis using the present data set. In this case, utility is solely comprised of a cost which accordingly needs to be minimized. We can represent this utility as the negative of , the cost to reach 10 cm with a given mass at a given duration:

|  |  |  |
| --- | --- | --- |
|  |  | (20) |

As shown earlier in Figure XX, the cost of reaching exhibits a U-shaped curve, initially decreasing with slower movements, but then increasing (Figure XX). The minimum of the curve indicates the optimal speed predicted by a utility that is solely dependent on the gross metabolic cost of reach; in this utility formulation there are no free parameters to fit to the preferred duration data.

We find that minimizing gross metabolic cost alone (i.e., maximizing, ) underestimates preferred movement durations, predicting significantly faster speeds than observed (SSE = 6.27e-2 (2a) , 1.33e -1 (2b), 1.975e-3 (2c)), and is also unable to explain differences in movement duration with target size across experiments. However, when looking at the changes in movement duration with added mass normalized to reaching with no added mass, minimizing gross metabolic cost alone does an excellent job (SSE = 1.91e-3 (2a) , 8.60e-4 (2b), 1.83e-2 (2c) ). Indeed, it performs like a utility-based capture rate where effort is represented as metabolic cost (SSE = 1.30e-3 (2a), 4.29e-4 (2b), 1.60e-2 (2c)). Thus, while minimizing gross metabolic cost alone does not predict absolute movement durations, it can explain changes in preferred movement speed with added mass.

**Net Metabolic cost:**

One can also consider the cost of reaching alone (no base metabolic rate), referred to as the net metabolic cost, as opposed to the gross metabolic cost reported above. Net metabolic rate is calculated as the gross metabolic rate , minus the resting metabolic rate: . From Eq. 2, we can then derive an expression for the net metabolic cost of a reach of a given mass and duration:

|  |  |  |
| --- | --- | --- |
|  |  | (21) |

The relation between net metabolic cost and movement duration also exhibits a minimum, representing the reach duration that would minimize net metabolic cost, and this duration also increases with added mass. However, the predicted durations are much higher than the durations that minimize gross metabolic cost. The coefficient () in equation 21 tells us that net metabolic cost has a much lower cost of time, and thus longer duration movements are penalized less. The best fit parameters for net metabolic cost were , , , and (SSE = 105365.4, AIC = 1741.31).

**Sum of squared torques:** In the field of movement neuroscience, computational models of reaching movements often use forms of effort other than metabolic cost to represent movement costs. One such approach is to quantify movement effort cost as the sum of squared joint torques required to generate the movement. In the ensuing analysis, we sought to determine whether a utility in which effort was represented as the sum of squared joint torques, rather than metabolic cost, could also explain the observed changes in preferred movement speed. To obtain an expression for sum of squared torque effort, , like that obtained for metabolic cost, we simulated participant-specific reaching movements with the mass and durations prescribed in Experiment 1. The required joint torques were backed out using inverse dynamics based on a planar two-link model of the arm and the effort rate of each movement was calculated as the sum of squared shoulder and elbow torques divided by the movement duration. Next, we fit an equation of similar form as Eq. 1, to parameterize the relationship between effort rate, represented as the sum of squared torques, and movement duration and mass:

|  |  |  |
| --- | --- | --- |
|  |  | (22) |

where (btorque = 0.042 ± 0.0079, itorque = 2.13 +/- 0.07, jtorque = 3.50 +/- 0.12, SSE = 98487.49, AIC = 1725.16). Notably, there are distinct differences between the two effort representations. The sum of squared torques increases quadratically with mass, in stark contrast to the near-linear growth observed in metabolic cost. We also are limited in that there is no accounting for a resting metabolic rate, as we only represent torques associated with the reaching movement, thus  is zero. Another consequence of only representing movement torques (as most computational models do) is that there is no cost associated with a zero velocity movement (or movement of infinite duration), thus the term equivalent to the time-invariant reach cost, a, in Eq. 1 is also zero and not included in Eq. 7. Replacing in Eq. 4 with , provides the following utility:

|  |  |  |
| --- | --- | --- |
|  |  | (23) |

Employing the same fitting procedure as described above and fitting a single parameter, , we find that the sum of squared torques does a significantly worse job in predicting the experimental data in all three experiments (Experiment 2a: alpha= 30.50, SSE = 0.495, AIC = ; Experiment 2b: alpha= 80.68, SSE = 0.368, AIC =; Experiment 2c: alpha= 26.891 , SSE = 0.597, AIC =) compared to when effort is represented as metabolic cost. This is true for both predictions of the absolute movement durations as well as the changes in movement duration with added mass (SSE = 3.85e-2, 3.56e-3, 1.25, for Experiments 2a,b, and c, respectively).

The lack of a resting cost in the sum of squared torques effort representation may have contributed to the poor fit to the data. To provide a more direct comparison of effort representations, we considered the net metabolic cost of the action, rather than the gross metabolic cost of the action. Gross metabolic cost is the sum total of metabolic expenditure required for an action and includes the cost of the movement as well as the cost of resting. Net metabolic cost is only cost associated with the movement, and is calculated as shown in Eq. . Substituting net metabolic cost (Eq. 3) for  in Eq. (5) and setting  to 0:

|  |  |  |
| --- | --- | --- |
|  |  | (24) |

, we find that the model performs similarly to a utility based on gross metabolic cost for both absolute (SSE = xx, xx, xx, for Experiments 2a,b, and c, respectively), and normalized movement durations (SSE = xx, xx, xx, for Experiments 2a,b, and c, respectively). It also appreciably outperforms the sum of squared torques model.

|  |
| --- |
|  |
| Figure |

**Accuracy:** It is possible that participants are adjusting their movement durations to maintain a fixed accuracy level. To examine this, we solved for the single probability that best predicted preferred movement durations across masses in experiments 2a and 2b. Experiment 2c was omitted from the analysis since it had negligible accuracy requirements and no stopping requirements. The best-fit probability was 0.9496 for Experiment 2a and 0.811 for Experiment 2b. These numbers are similar to the average success probabilities measured for each experiment (xx and xx, respectively), and also captures the reduction in probability of success with the smaller target in Exp. 2b. However, in the experiments, actual success probability was not the same across added mass, but varied, especially in Exp 2b. Thus, compared with a utility based on capture rate, this accuracy-based model performed worse in predicting participants’ preferred durations in both experiments, as evidenced by higher SSEs and AIC scores (SSEs: 3.59e-3 (Exp. 2a), 1.46e-2 (Exp. 2b), AICs: -26.1 (Exp. 2a), -20.5 (Exp. 2b)).