

Planning multiple movements within a fixed time limit: The cost of constrained time allocation in a visuo-motor task

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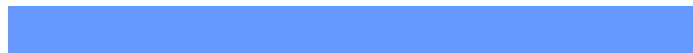
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S.-W. Wu, M. F. Dal Martello, and L. T. Maloney (2009) evaluated subjects' performance in a visuo-motor task where subjects were asked to hit *two* targets in sequence within a fixed time limit. Hitting targets earned rewards and Wu et al. varied rewards associated with targets. They found that subjects failed to maximize expected gain; they failed to invest more time in the movement to the more valuable target. What could explain this lack of response to reward? We first considered the possibility that subjects require training in allocating time between two movements. In Experiment 1, we found that, after extensive training, subjects still failed: They did not vary time allocation with changes in payoff. However, their actual gains equaled or exceeded the expected gain of an ideal time allocator, indicating that constraining time itself has a cost for motor accuracy. In a second experiment, we found that movements made under externally imposed time limits were slower than movements made under self-imposed time limits and that subjects pursued different motor strategies with distinct speed–accuracy tradeoffs in different conditions.

Keywords: Bayesian decision theory, expected utility, optimality, Fitts' Law, reaching, touching

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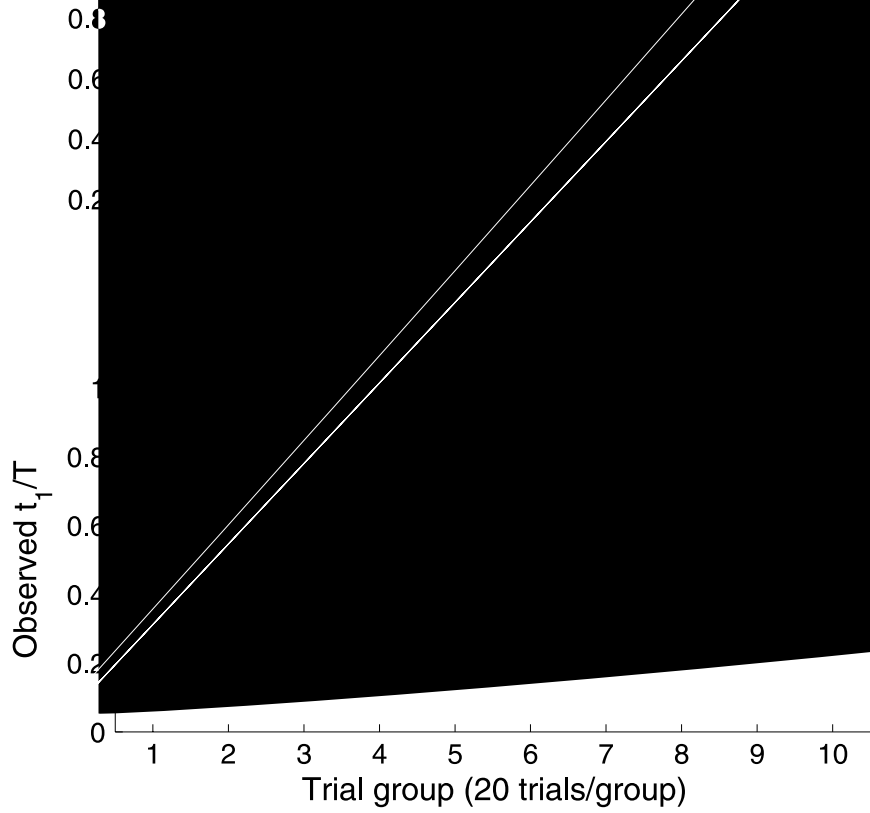
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The ability of constrained time training

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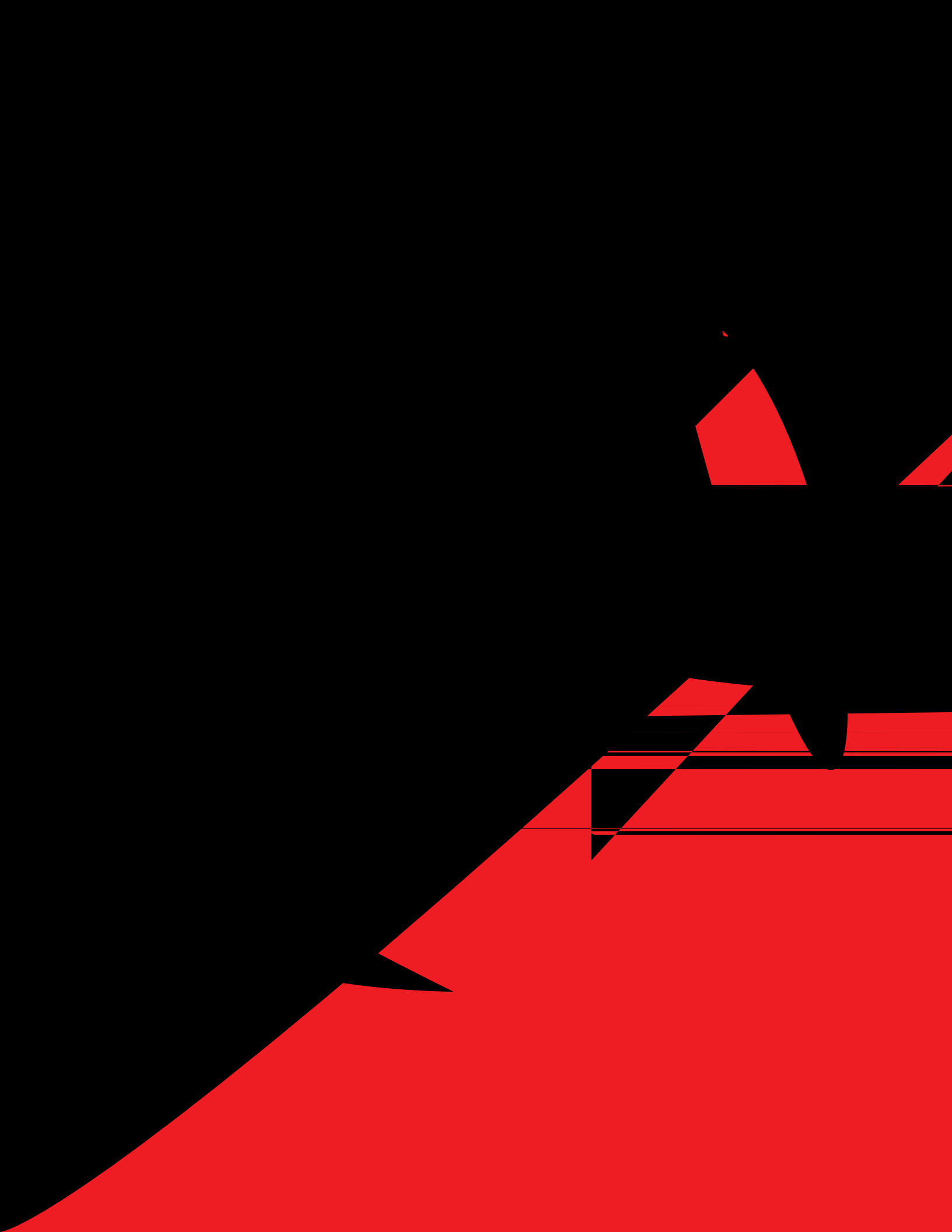
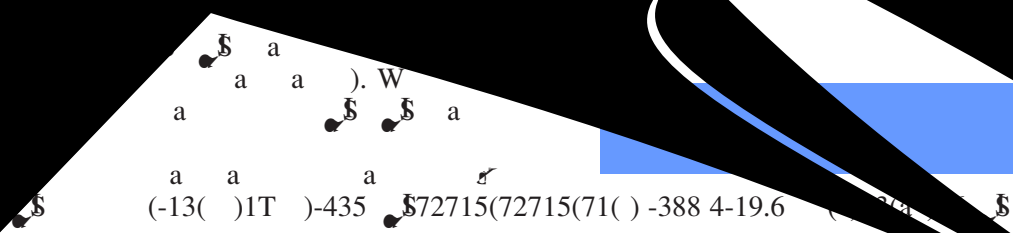


Figure 7. Efficiency for subjects in the test session. The error bars mark 95% confidence intervals (Bonferroni corrected for three conditions).





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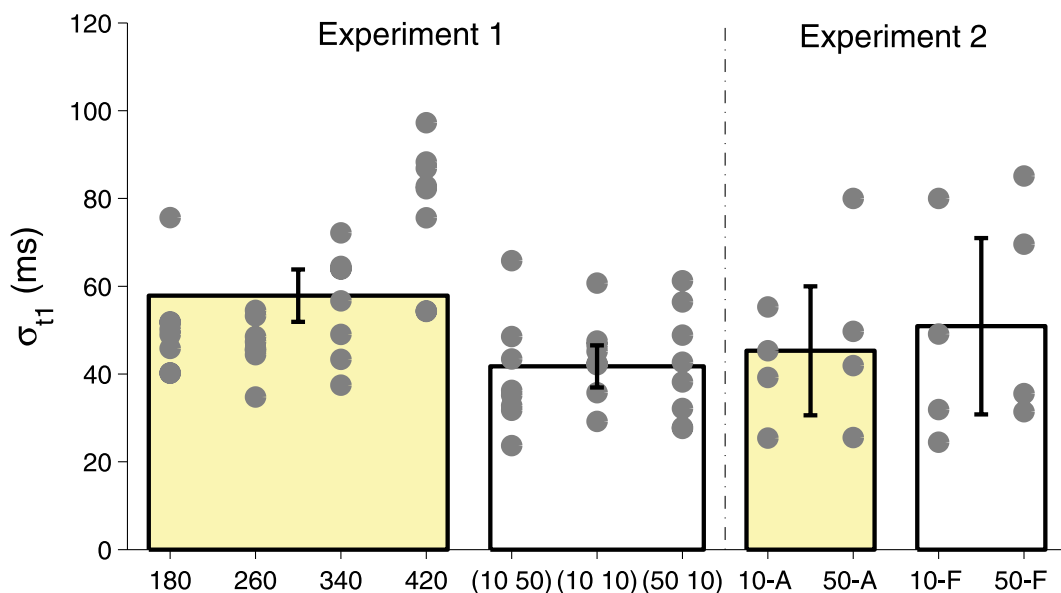
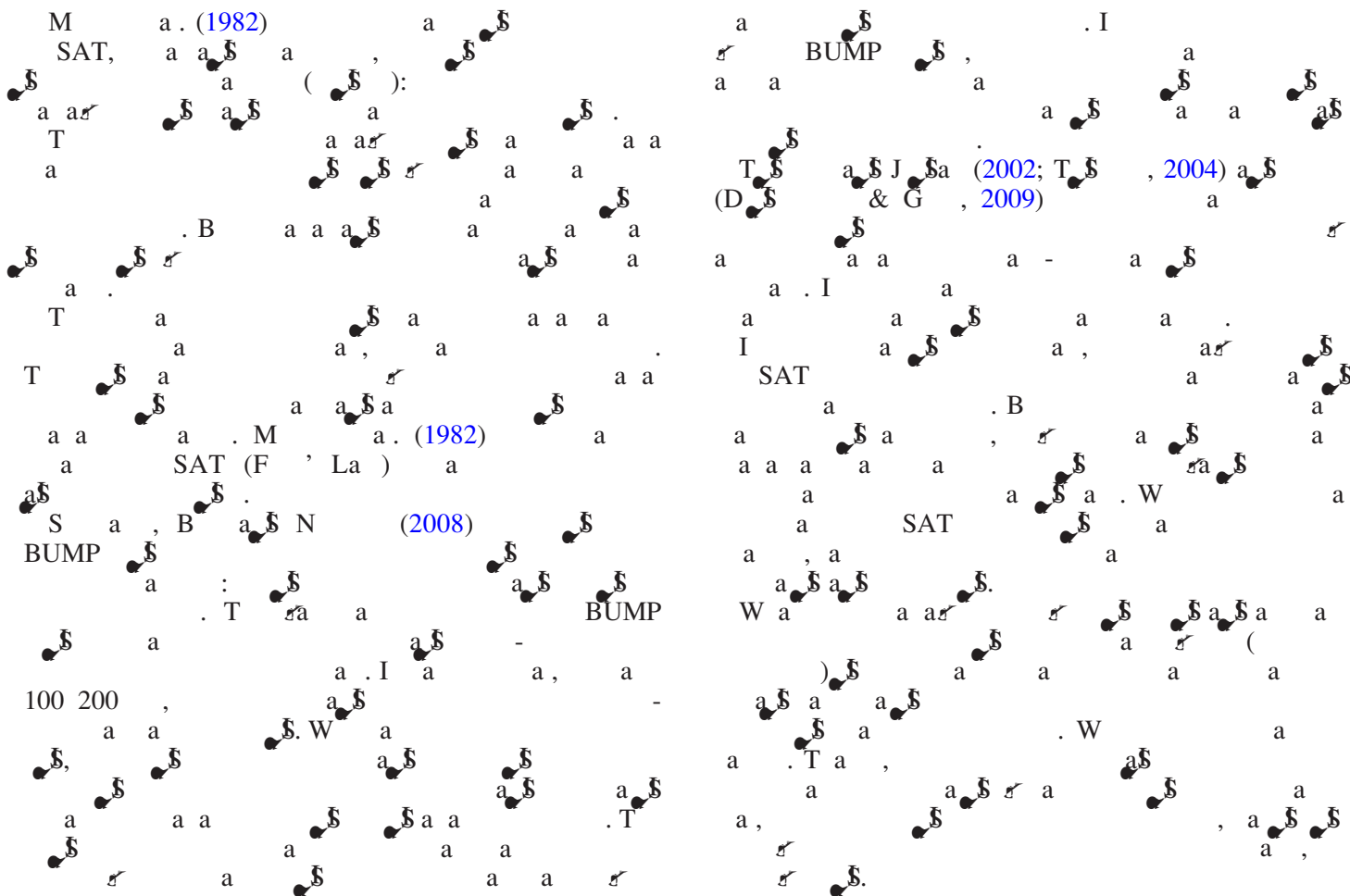


Figure 11. Temporal movement uncertainty. The standard deviation of t_1 . The effort to constrain t_1 to a specified time window, as in the constrained timing conditions of Experiment 1 or 2, did not lead to a smaller standard deviation than when there was no need to control t_1 . Each gray dot above a condition of Experiment 1 or 2 denotes the data of a subject under that condition. The bars shown serve to group conditions. The height of each bar is the mean across the conditions grouped. Yellow bars group the constrained timing conditions. White bars group the choice timing conditions. The error bars mark the 95% confidence intervals of the means.



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