*Research Article*

# Overconfidence in an Objective Anticipatory Motor Task

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ABSTRACT—*Overconfidence can place humans in hazardous situations, and yet it has been observed in a variety of cognitive tasks in which participants have to rate their own performance. We demonstrate here that overconfidence can be revealed in a natural and objective visuo-motor task. Participants were asked to press a key in synchrony with a predictable visual event and were rewarded if they succeeded and sometimes penalized if they were too quick or too slow. If they had used their own motor uncertainty in anticipating the timing of the visual stimulus, they would have maximized their gain. However, they instead displayed an overconfidence in the sense that they underestimated the magnitude of their uncertainty and the cost of their error. Therefore, overconfidence is not limited to subjective ratings in cognitive tasks, but rather appears to be a general characteristic of human decision making.*

Overconfidence refers to the human tendency to overestimate one's own abilities and knowledge (Alpert & Raiffa, 1982; Oskamp, 1965). Overconfidence is believed to have dramatic consequences in such diversified areas as warfare (Johnson et al., 2006), stock-exchange trading (Statman, Thorley, & Vorkink, 2006), and driving (Svenson, 1981). One methodological difficulty that has hampered research in this field, to the point that the very existence of overconfidence has been challenged (Ayton & McClelland, 1997; Gigerenzer, Hoffrage, & Kleinbölting, 1991; Keren, 1988; Koriat, Lichtenstein, & Fischhoff, 1980), is the reliance of previous studies on self-report measures. Up to now, it has been difficult to avoid using such subjective measures to study this form of knowledge about knowledge, or metacognition (Metcalfe & Shimamura, 1994). The problem with subjective reports is that they can be imprecise and strongly biased (Adams & Adams, 1961). We report here the results of an objective paradigm revealing overconfidence in a simple motor action.

Planning of motor movements often requires accurate timing. A tennis player who masters all the right movements but who times them a bit too early or too late will see all the balls go outside the court. Similarly, a violinist needs to be synchronized with the rest of the orchestra. Such sensorimotor interactions have been studied in tapping experiments in which participants have to synchronize a repetitive motor act with a repetitive sensory stimulus (Aschersleben, 2002; Fraisse, 1966; Wing, 2002). In the study reported here, we reduced sensorimotor synchronization to its simplest form by asking our participants to synchronize a single motor action with the anticipated time of a visual event.

Participants had to press a key at the time of the last visual event in a sequence of three. The events were presented at a constant pace, so that participants could estimate the timing of the last event relative to the second one by reproducing the temporal interval between the first two events. To keep uncertainty in this visual timing to a minimum, we kept this interval (stimulus onset asynchrony, SOA) constant (0.5 s) throughout the experiment. The visual display consisted of the successive presentation of pairs of dots at the vertices of a virtual hexagon (see Fig. 1). It is important to emphasize that participants had to anticipate the timing of the last pair of dots; if they simply reacted to the presentation of the completed stimulus, they would always be too late by a few hundred milliseconds.

To measure participants' confidence in their performance of this task, we needed to introduce a risk factor. If participants responded accurately within a narrow temporal interval, they received 100 points. In addition, depending on the condition shown graphically at the beginning of the trial, they might lose 200 points if they were too fast or too slow. Thus, three experimental conditions were intermixed: no-penalty, late-penalty, and early-penalty conditions.

There was an optimal time at which participants should have anticipated the onset of the final visual event in order to maximize their gain. This optimal time was a function of their motor variability and the potential cost of their action. Consider, for example,

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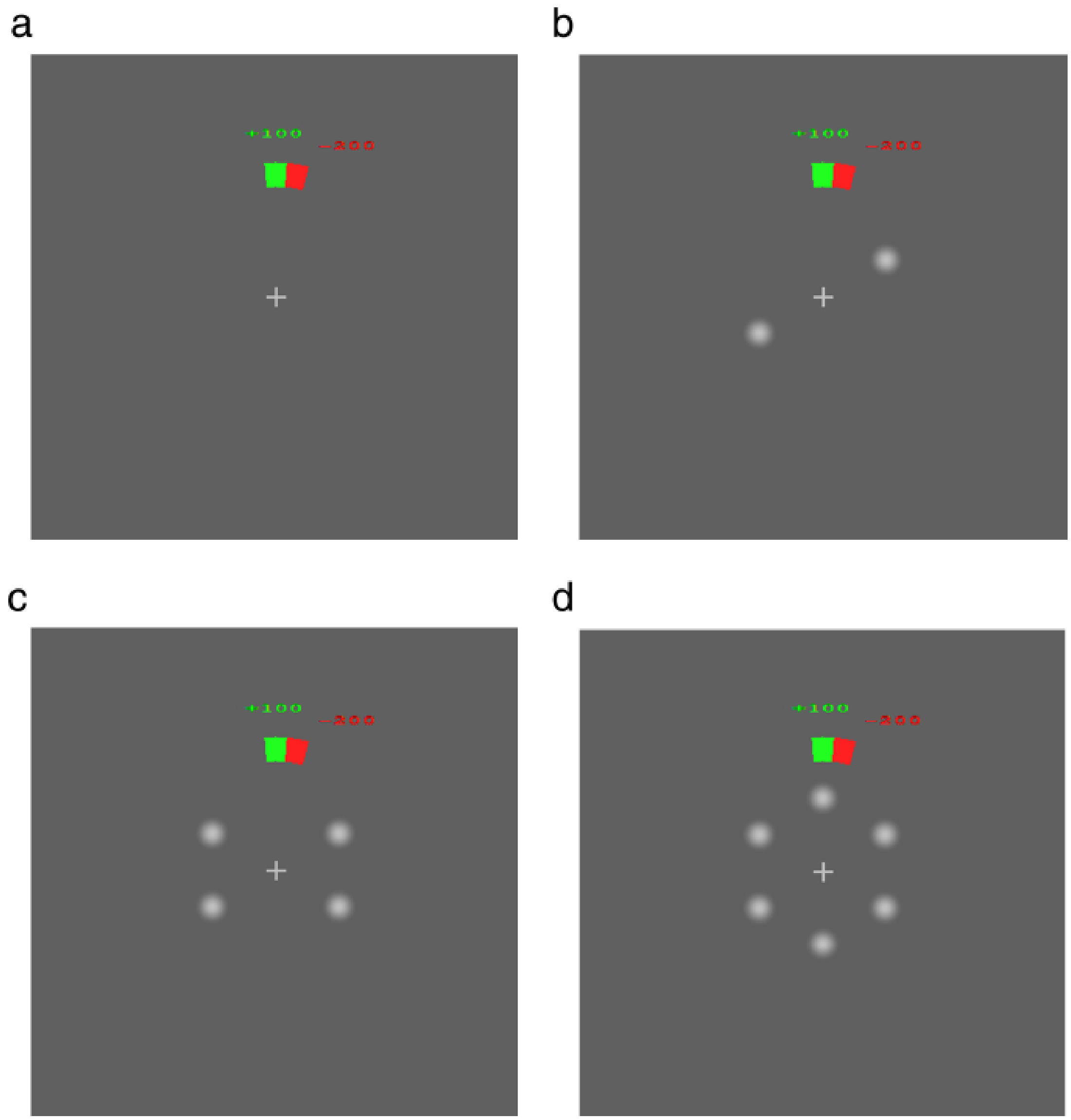


**Fig. 1.** Illustration of the display sequence. The completed stimulus consisted of six dots displayed at the vertices of a virtual hexagon. The dots were presented in pairs, each pair consisting of dots at opposing vertices. The stimulus onset asynchrony (SOA) between the first two pairs equaled the SOA between the last two pairs (500 ms). Participants were instructed to maximize their gain by hitting a key simultaneously with the presentation of the last pair of dots. On each trial, they gained points if they hit the key during the reward interval, and in some conditions they lost points if they hit the key during a penalty interval. These intervals were displayed graphically as small colored segments (green for reward and red for penalty) around the hexagon. Because the dots were presented in a clockwise manner, a red region to the right of the green one represented a late penalty, as illustrated here. The width of each colored region was indicative of the length of the temporal interval; each successive pair of dots in the display represented a rotation of 60° over an interval of 500 ms, so a 50-ms reward or penalty period was indicated by a region of 6°. The number of reward or penalty points was written next to the corresponding colored region.

the late-penalty condition. In this case, the utility function $u(t)$ was a reward region that was 50 ms long and centered on 1 s (twice the SOA), followed by a penalty region that was also 50-ms long (see Fig. 2, top row):

$$\begin{cases} u(t) = 100 & \text{if } t \in [975,\ 1{,}025], \\ u(t) = -200 & \text{if } t \in [1{,}025,\ 1{,}075], \\ u(t) = 0 & \text{otherwise.} \end{cases}$$

Note that in this task, hitting uncertainty is well modeled as a Gaussian distribution, $h(t)$, that is centered on zero and has a standard deviation $\sigma_I$ (the subscript “I” reflects the fact that the source of noise is internal). In contrast, in reaction time studies, an action is triggered as quickly as possible in response to a sensory stimulus, and time distributions are characteristically skewed (Luce, 1986). The expected gain in our task is simply the convolution of hitting uncertainty with the utility function

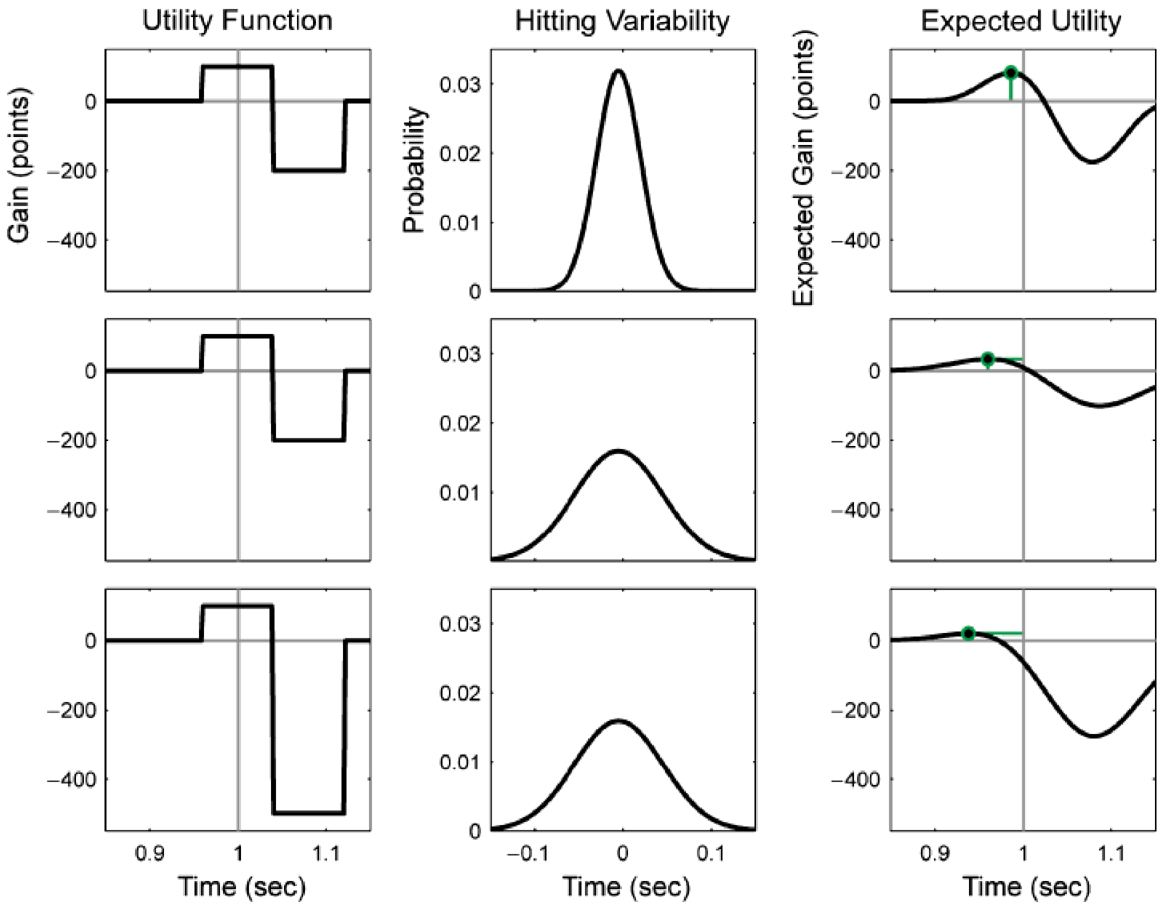


**Fig. 2.** Model predicting optimal hitting time in the anticipatory motor task. The top row explains the predictions for the late-penalty condition, given a participant whose motor uncertainty is a Gaussian distribution with a standard deviation of 25 ms. The graph on the left shows the utility function in this condition, that is, the number of points to be gained as a function of the timing of the key press. The graph in the middle shows the hitting variability of this participant when aiming at a target presented at time zero. The graph on the right shows the resulting expected utility of this participant as a function of the hitting time that the participant is aiming for. When there is a penalty for pressing the key shortly after the target event, which occurs 1 s into each trial, a participant should aim to hit the key a bit earlier than 1 s in order to maximize gain, as shown by the green dot. The early-penalty condition has the mirror-symmetric utility function, and therefore the mirror-symmetric expected utility. No time shift is expected in the no-penalty condition. The middle row presents corresponding graphs for a participant whose motor uncertainty is twice as large as in the top row and for whom the utility function is the same. The bottom row presents corresponding graphs for a condition in which the late penalty is increased from 200 to 500 points. When hitting variability is increased (middle row), the anticipation should be increased, and when the penalty cost increases (bottom row), the anticipation should be greater still.

(Mamassian, Landy, & Maloney, 2002; Trommershäuser, Maloney, & Landy, 2003):

$$g(t) = h(t) * u(t).$$

Expected gain reaches a maximum value $g^*$ at time $t^*$, the optimal hitting time:

$$t^* = \arg\max_t(g(t))$$
$$g^* = g(t^*)$$

In the late-penalty condition, this optimal time was earlier than the center of the reward region in order to minimize the number of times hits would fall in the penalty region. The larger the spread of hitting uncertainty, the earlier the optimal time (Fig. 2, second row). Similarly, with a larger penalty, the optimal time would have been earlier (Fig. 2, last row).

## METHOD

### Participants

Participants were volunteers from the community around the research laboratory. The design of the experiment received approval from the institutional review board, and all 10 participants gave their informed consent. Their age ranged from 23 to 54 years ($M = 32$).

### Apparatus and Stimuli

Each visual stimulus was presented in three consecutive events on a 21-in. CRT monitor running with a 60-Hz refresh rate. Each event consisted of the presentation of a pair of highly visible Gaussian blobs located at the vertices of a virtual hexagon. The SOA between the first two events equaled the SOA between the last two events and was fixed at 500 ms throughout the experiment.

### Procedure

Participants were instructed to press a key simultaneously with the completion of the visual stimulus (i.e., the third event). If they pressed the key accurately within a narrow temporal interval (i.e., within the 50-ms interval centered around the third event), they received 100 points. In addition, in the penalty conditions, they lost 200 points if they were too slow or too fast. In the early-penalty condition, the penalty was imposed if they pressed the key 75 to 25 ms before the third event, and in the late-penalty condition, the penalty was imposed if they pressed the key 25 to 75 ms after the third event. The condition was shown graphically at the beginning of each trial. Participants started each session of 30 trials (10 trials of each of the three penalty conditions, in a randomized order) with 5,000 points and were instructed to maximize their gain. They received visual feedback after each trial. The feedback information consisted of their current score and the message "Too Late" or "Too Early" if their hit fell outside the reward interval. Participants completed 20 such sessions, divided into four consecutive blocks. They were allowed to take short breaks between blocks (without leaving the room).

To find the optimal hitting time, participants required knowledge of the utility function (which was symbolically provided before each trial), as well as their own internal hitting uncertainty. This optimal time could be computed from the model presented in the introduction. We checked the normality of hitting variability using a QQ plot of the data against the standard normal distribution (Evans, Hastings, & Peacock, 2000).

## RESULTS

Mean hit times in all three penalty conditions are illustrated in Figure 3a. The figure shows hit times averaged across all 10 participants.[1] Hit times were characteristically too late at the beginning of the experiment and gradually became less biased during later sessions; the effect of session on hit times was significant, $F(19, 38) = 4.81, p < .001$. The initial motor delay may reflect an overestimation of the interval between the first two events of the visual stimulus. Such a bias toward overestimating the duration of the first interval in a sequence relates to a classical phenomenon called time-order error (Allan, 1977). The reduction of this bias over time reflects a recalibration of the visuo-motor system.

Mean hitting times in the three penalty conditions differed significantly, $F(2, 38) = 65.3, p < .001$. As expected, the early-penalty condition generated later hitting times compared with the no-penalty condition, and the late-penalty condition generated earlier hitting times compared with the no-penalty condition. Thus, participants were able to appropriately take into account the type of penalty, at least in a qualitative way.

To determine how efficient participants were in face of the various penalty conditions, we needed to estimate their individual variability in hitting time. Figure 3b shows hitting-time variability across sessions. It is clear that as sessions went by, participants' variability decreased, $F(19, 38) = 2.17, p = .021$. As a result of this motor learning, the standard deviation of the distribution of hitting times shrank from 40 ms at the beginning of the experiment to 29 ms at the end. In addition, all three penalty conditions were associated with the same variability, $F(2, 38) = 1.86, p = .169$. In particular, the early- and late-penalty conditions did not generate larger variability than the no-penalty condition, as would be expected if participants were trying to figure out the optimal strategy by trial and error. Therefore, in the model we used to predict optimal behavior, we pooled the estimate of hitting variability across all three penalty conditions.

Once we knew the hitting variability for a given participant and session, we were able to compute the expected optimal behavior for that participant and that session according to the model described earlier (see Fig. 2). From this model, we computed both

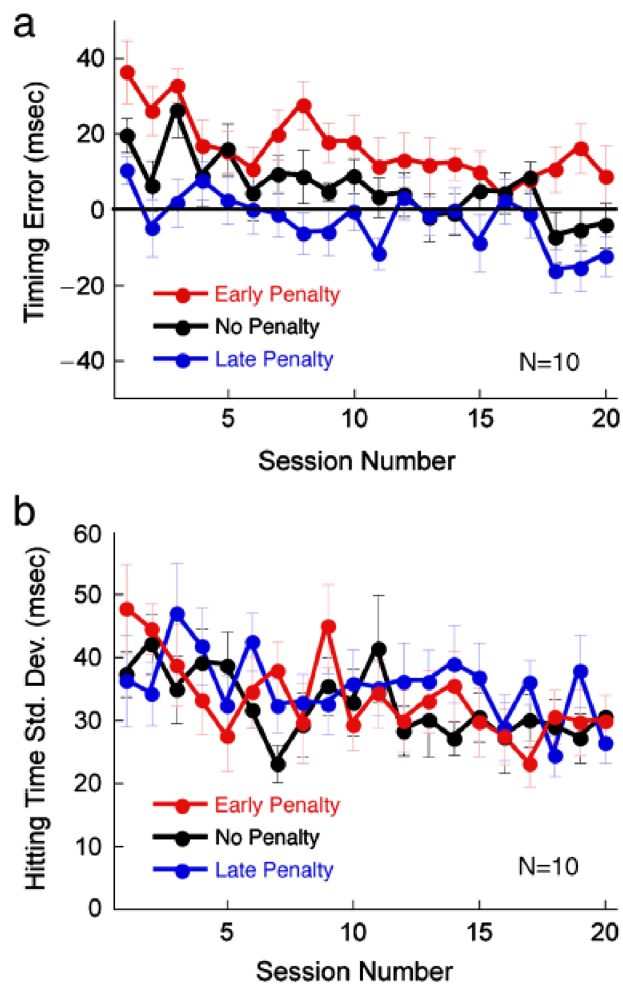


**Fig. 3.** Mean (a) timing error and (b) standard deviation of hitting times as a function of session. Timing error was calculated as the time difference between the motor action and the last visual event. Standard deviation of the hitting times is a measure of the motor uncertainty of the participants. In each graph, results are shown separately for the three penalty conditions. Error bars indicate standard errors across participants.

[1]Individual participants' data are included in the supplementary materials available on-line (see p. 606).

the expected score and the shift in hitting time that would lead to maximum gain. Figure 4a shows both expected and actual scores, averaged across participants. Given that hitting variability decreased across sessions, the expected scores increased over the course of the experiment; across the four blocks of sessions, the increase was significant, $F(3, 16) = 10.3, p < .001$. The reduction in hitting variability also induced a significant increase in the actual scores across sessions, $F(3, 16) = 11.4, p < .001$. Expected and actual scores increased at the same rate. However, participants' scores started and remained significantly below the expected scores, paired $t(19) = 11.4, p < .001$. In other words, even though participants became gradually less variable, they did not learn how to avoid the penalty periods.

The expected time shift relative to the no-penalty condition was positive in the early-penalty condition (i.e., participants should have delayed their hitting time a bit) and negative in the late-penalty condition (i.e., participants should have sped up their hitting time a bit). Because of the symmetry in the design of the experiment and the symmetry in hitting variability, these two expected shifts were equal in absolute value and can therefore be represented as a single prediction (see Fig. 4b). Given that the variability in hitting time decreased across sessions, the predicted time shift also decreased across sessions, $F(3, 16) = 11.3, p < .001$. Similarly, the absolute values of the measured shifts, taken from the data shown in Figure 3a, did not differ between the early- and late-penalty conditions and were therefore combined into a single measured shift for each session. Across sessions, these mean measured shifts were significantly larger than zero, $t(19) = 9.33, p < .001$ (one-tailed), confirming that the hitting times in the penalty conditions did differ from hitting times in the no-penalty condition. However, the mean measured shifts did not vary significantly across sessions, $F(3, 16) = 0.52, p = .673$. In addition, they differed significantly from the expected shifts, paired $t(19) = 10.4, p < .001$. In other words, the results for time shifts confirmed the results for scores. Even though participants became gradually less variable in their motor behavior, their strategy in dealing with early and late penalties remained suboptimal.

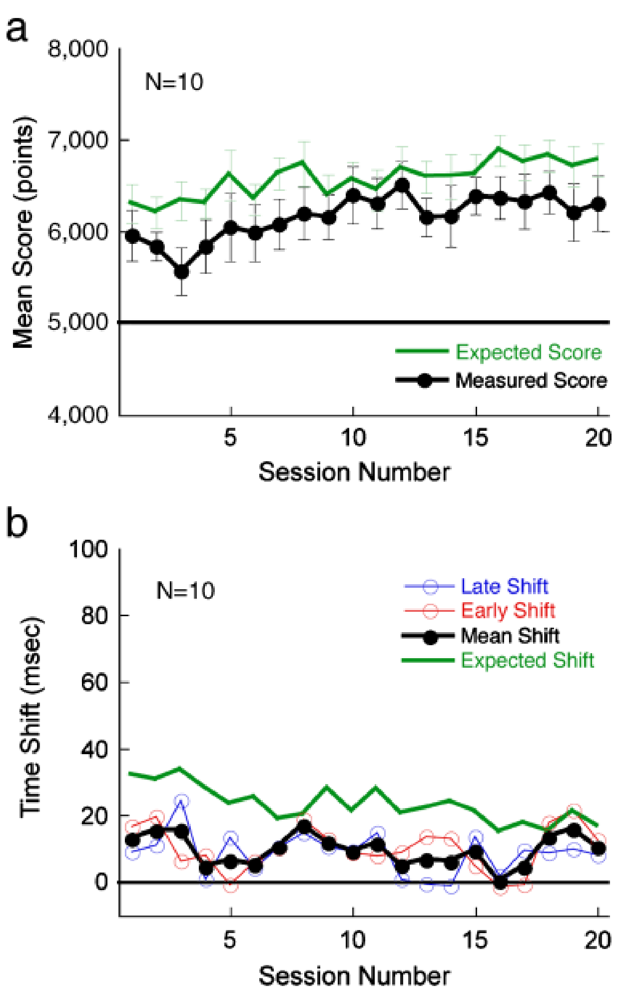


**Fig. 4.** Expected and actual (a) scores and (b) time shifts as a function of session. Participants started each session with 5,000 points. Expected scores were computed from the model illustrated in Figure 2 and the motor uncertainty of each participant taken separately. Error bars represent standard errors across participants. Time shift was calculated as the difference in timing error between the early-penalty and no-penalty conditions (early shift) or between the no-penalty and late-penalty conditions (late shift). The mean time shift is the average of the late and early shifts. The expected time shift was computed from the model. Mean shifts smaller than the expected shift represent overconfidence.

## DISCUSSION

The early- and late-penalty conditions induced participants to shift the timing of their hits away from the timing in the no-penalty condition, but participants did not shift their hitting times enough. According to the model presented in the introduction (see Fig. 2), there are two possible reasons why participants' performance was suboptimal: They either underestimated their own motor variability or underestimated the effective cost of the penalty periods. Both of these reasons can be characterized as overconfidence in the face of visuo-motor risk. Participants undervalued some explicit knowledge (the magnitude of the cost) or some implicit knowledge (the variance of their hitting uncertainty).

In a first attempt to disentangle these two possible sources of overconfidence, we conducted two further experiments.[2] In one experiment, without telling the participants, we artificially increased their motor variability during the middle 10 sessions by adding external noise to their responses before feedback was provided. The external noise in each trial was sampled from a zero-mean Gaussian distribution with a 50-ms standard deviation. To maximize their scores, participants should have tried to estimate their new effective variability and increased their time shifts accordingly. Although our manipulation produced a dramatic change in the expected time shifts, it had no effect on the measured time shifts. Therefore, it seems that participants were reluctant to update their estimates of their own uncertainty. Looking at the participants' behavior after we suppressed the

[2]These experiments are discussed in more detail in the supplementary materials available on-line (see p. 606).

added noise, we saw no effect of the exposure to a large increase in effective uncertainty, a further indication that participants did not change their estimates of their own uncertainty during the added-noise period.

In the other experiment, we imposed a larger penalty of 500 points during the middle 10 sessions. This time, participants were clearly aware of the manipulation. Both the expected and the measured time shifts increased over the period when the penalty was increased, but the measured shifts remained largely smaller than the expected ones. Therefore, it seems that participants dealt with a change in cost slightly better than they dealt with a change in variability. Although other studies have found that people can adapt very well to different cost functions (Trommershäuser et al., 2003), the relative inefficiency of our participants in adjusting their behavior might reflect the difficulty of converting a cost value presented symbolically into something meaningful for the motor system.

Our results provide a clear demonstration of overconfidence in an anticipatory motor task. Participants did take into account the costs of responding too quickly or too late, but their adjustments were not optimal. Their overconfident behavior came from limited knowledge about their motor timing uncertainty and also, but to a lesser extent, from difficulties in translating a cost magnitude into an appropriate action. It may be that the ability to adjust hitting times appropriately to experimental conditions is one of those behaviors that cannot be learned (Breland & Breland, 1961), or that our participants simply lacked enough training to perform near-optimally (Körding & Wolpert, 2004). Even if that behavior could be learned, it would remain interesting that it did not change over the course of the experiment, even though motor learning did take place, as indicated by the reduction in hitting variability. Therefore, overconfidence is not limited to the realm of subjective beliefs and cognitive judgments, but appears instead to reflect a general characteristic of human decision making.

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**SUPPLEMENTARY MATERIAL**

The following supplementary material is available for this article:

Individual Differences and Supplementary Experiments

This material is available as part of the on-line article from http://www.blackwell-synergy.com/doi/full/10.1111/j.1467-9280.2008.02129.x (this link will take you to the article's abstract).

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