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RESEARCH REPORT

Self-serving dishonest decisions can show facilitated cognitive dynamics

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Abstract We use a novel task to test two competing hypotheses concerning the cognitive processes involved in dishonesty. Many existing accounts of deception imply that in order to act dishonestly one has to use cognitive control to overcome a bias toward the truth, which results in more time and effort. A recent hypothesis suggests that lying in order to serve self-interest may be a rapid, even automatic tendency taking less time than refraining from lying. In the current study, we track the action dynamics of potentially dishonest decisions to investigate the underlying cognitive processes. Participants are asked to privately predict the outcome of a virtual coin flip, report their accuracy and receive bonus credit for accurate predictions. The movements of the computer cursor toward the target answer are recorded and used to characterize the dynamics of decisions. Our results suggest that when a self-serving condition holds, decisions that have a high probability of being dishonest take less time and experience less hesitation.

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Introduction

We have all been the victim of deception, and given the pervasiveness of little lies (DePaulo et al. 1996), on any given day most of us are also perpetrators. Deception appears to be a surprisingly common component of everyday social interactions (DePaulo et al. 1996; DePaulo and Kashy 1998). Inevitably, some individuals choose dishonesty over the truth because they find an advantage in lying. People are tempted to lie when it serves their self-interest, be it financial, social or emotional. But even so, the question remains: In a tempting situation where being dishonest serves one's self-interest, is it easier for people to lie than stay honest, or is lying always more cognitively complex?

The answer to the above is not obvious and has been the target of some debate, touching on issues in judgment and decision making about quick and intuitive processes versus slower and deliberative ones.[1] There are at least two relevant theories that would seem to address the underlying processes of dishonest decisions. One view, stemming from Spinoza's hypothesis about an inevitable truth bias in human belief system (Gilbert 1991), suggests that honesty is the grounded process and is therefore more accessible and immediate. From this perspective, in order to act dishonestly, one first has to overcome a truth bias, resulting in

1 These two notions of fast versus slow processes have had broad influence on social cognitive for decades (e.g., recently, see Kahneman 2011) and have also been discussed in the domain of deception by Seymour and colleagues (Seymour 2001; Seymour and Schumacher 2009).

more time and effort (Duran et al. 2010; Duran and Dale 2012; McKinstry et al. 2008; Spence et al. 2001). Indeed, most theories of the mechanisms underlying deception imply that lying is more cognitively costly (Vrij et al. 2008; Verschuere and De Houwer 2011). Those who espouse this view do not often make explicit claims regarding precise underlying mechanisms of deception (e.g., whether more implicit or deliberative). Yet many accounts referenced above, perhaps the most common accounts, involve a more or less subtle implication that cognitive processes underlying deception are strategically (and thus more slowly) deployed in order to serve self-interest.[2]

There is, however, another theoretical possibility. A more recent line of research argues that dishonesty can be greatly facilitated, perhaps even be "automatic," and therefore will be the first and easier choice in any tempting situation where lying pays. This hypothesis predicts that people will need more time and self-control while being honest and refraining from cheating (Shalvi et al. 2012). It is also consistent with the literature concerning how depletion of self-control can increase the chance of performing dishonestly (Gino et al. 2011; Mead et al. 2009) and the effect of sleep deprivation on self-serving dishonesty (Barnes et al. 2011).

In support of the first hypothesis that lying requires more cognitive effort, Spence et al. (2001) used a behavioral and functional imaging study to show that lying takes significantly more time and results in reliable activation within regions of the ventrolateral prefrontal cortex. Spence et al. note this area is associated with conditional learning and response inhibition. In humans, a lesion in this region can be associated with failure to inhibit responses. One possible explanation, given the data, is to relate the activity in these regions to the withholding of the truth, which is an inhibitory function.

Moreover, in studying action dynamics of false responding, Duran et al. (2010) report increased complexity of arm movements in false responding relative to truthful responding. In their experiment, participants were instructed to answer autobiographical questions falsely or truthfully by navigating a Nintendo Wii Remote to NO or YES regions on a projector screen. The results revealed that during false responses, the arm movement trajectories were slower and more curved toward the competitor true response. This suggests the existence of a truth bias that makes it more difficult and time-consuming to produce a false response.

[2] However, many theories imply the involvement of cognitive control and related resources in order to deceive, which implies more deliberative processes (see: Walczyk et al. 2003; Seymour and Schumacher 2009).

Yet some new behavioral work has supported the second hypothesis, at least in some experimental contexts. Shalvi et al. (2012) have presented a study showing that dishonesty can in fact be the facilitated, rather than the more cognitively costly, response. Given that under time pressure people are forced to act as dictated by their more accessible tendencies, Shalvi et al. suggest that, in a situation where one is tempted to lie and is also under high time pressure, one will more likely choose to lie. Participants were instructed to privately roll a die and self-report the outcome. They were rewarded based on how high the reported number was. The results revealed that participants who were assigned to high time-pressure condition tended to report bigger numbers at a considerably higher rate. The authors conclude that when lying pays, people will automatically choose dishonesty over truth unless they have enough time to deliberately refrain from lying. Another recent study on the role of deliberation and contemplation on dishonesty shows that having time to introspect in a deception game could result in greater honesty (Gunia et al. 2012).

Additional evidence is provided by Greene and Paxton's (2009) study on the neural bases of honest and dishonest choices. The authors designed a behavioral paradigm to investigate people's decisions when offered an opportunity to cheat. In the critical condition, given a chance to cheat, participants were asked to privately predict the outcome of random computerized coin flips. They were rewarded or lost points based on self-reported accuracy of their prediction. Subjects' brains were scanned using fMRI while completing the task. When there was an opportunity to cheat, honest subjects exhibited no additional processing in control-related brain regions (i.e., anterior cingulate cortex, dorsolateral and ventrolateral prefrontal cortex). Conversely, dishonest participants showed additional processing when cheating and when refraining from cheating. The authors suggest that the additional control activity in the liars' brain when they respond honestly (refrain from lying) is not related to overcoming a truth bias. Rather, it shows that when temptation is present it takes extra effort and control to be honest. The results were further supported in a recent follow-up study, which showed that variation in automatic processing is associated with the tendency to be honest (Abe and Greene 2014).

The current study

Variables often measured in deception studies (e.g., reaction time or the final answer provided by participants) reflect only the end point of a long cognitive process. In order to achieve more information about this longer process, we wished to "peel back" the cognitive processing that gives way to either an honest or dishonest response. One way to observe gradual changes in this competition is to explore action dynamics of the process. It has been shown that spatial and temporal dynamics of motor movements can shed light on the progression of high-level cognitive processes such as decision making (for reviews see Spivey and Dale 2006; Song and Nakayama 2008; Freeman et al. 2011; Freeman and Ambady 2009). This growing line of research on action dynamics suggests that decision-making outcomes are not first processed in the brain before being sent downstream to be expressed in motor subsystems. Instead, the ongoing competition between alternative options is captured concurrently in a person's overt movement dynamics. Thus, by studying the micro-behavioral properties of an unfolding decision, such as eye movements or reach movements, we might be able to get a sense of the underlying cognitive processes. Specifically, the decreased competition thought to be associated with self-serving lies, or the increased competition hypothesized to be present in temptation, can now be directly observed. This is important given that these processes are now only inferred, leaving unanswered issues concerning the time course of competition resolution, or even the nature of the competition itself (Magnouson 2005). The temporal sensitivity of action dynamics is thus poised to provide new insights into how response competition is resolved on a moment-by-moment basis. In anticipating these conclusions, we provide evidence that sources of competition from truth and deception are activated in parallel and resolved continuously over time—systematically modulated by high-level intentional states. These findings support a general view of cognition as the graded activation of mental states, extended to domains of complex social decision making (see Freeman et al. 2011, for similar attempts).

In the current study, we apply action dynamics to investigate people's behavior when they are naturalistically tempted to act dishonestly (as opposed to being explicitly instructed to do so). This allows us to study dynamics of a cognitive process leading to genuine dishonesty (extending Duran et al. 2010). Inspired by Greene and Paxton (2009), in the current study participants were rewarded for their self-reported accuracy in predicting a virtual coin flip. The movements of their mouse cursor while reporting their accuracy were recorded and used to illustrate the differences between honest and dishonest decisions. If honesty is the default process, people who behave dishonestly are expected to have mouse trajectories that, although end at the deceptive answer, are curved toward the competing truth response—demonstrating the hesitation and extra effort needed for overcoming the truth bias. On the other hand, if dishonesty is specially facilitated in a self-serving situation, dishonest people will directly choose the rewarding option even though their prediction was not accurate.

Experiment 1

Method

In Experiment 1, participants were asked to predict the outcome of a virtual coin flip. They predicted privately and, after observing the actual outcome of the coin flip, reported their accuracy by clicking on one of the two options on top left or top right of the screen (i.e., Correct or Wrong). The movements of the mouse cursor toward the target answer were recorded and used to characterize the dynamics of decisions that are likely to be dishonest. We programmed an online Adobe Flash-based game that has been posted on Amazon's Mechanical Turk (AMT), a web-based crowd-sourcing platform. Experimenters (i.e., "Requesters") can post their designed task on AMT where participants (i.e., "Workers") can sign up and take part in the uploaded task. Workers are paid for completing the task. Although it is common to collect a large sample size in AMT studies, we used a pilot version of the experiment to estimate the effective sample size for the study. Moreover, a rough power analysis was run to find the required number of observations.[3]

Participants and procedure

Ninety-seven participants were recruited online through Amazon's Mechanical Turk. Participation was restricted to people located in the USA, and participants were paid $0.40 for their time. Researchers used a numeric code on the server to ensure that participants had actually completed the task, and approved their payment on AMT.

Participants were instructed to predict the outcome of 20 consecutive coin flips with a certain pattern to the sequence of heads and tails, which they may or may not notice. They were asked to report their accuracy after each coin flip and were informed that they would win a bonus for each correct prediction. Participants were led to believe that we were interested in how receiving a reward while making private guesses can influence implicit learning of the underlying patterns. As we were interested in automatic and natural response tendencies, it is critical that participants do not become self-conscious about their moral decisions. Moreover, an important aspect of a mouse-tracking study is to observe the unintentional expression of mental processes in the action dynamics. Thus, the main purpose of the study

[3] The work we report here is novel enough that it is difficult to run a standard power analysis from past work. We piloted versions of this study to assess roughly the number of participants needed to obtain potential effects. We followed this study up with a replication. Though, in each, patterns of results vary, in general the findings are consistent (please see the Online Resource for a full report of the replication results).

was initially concealed from the participants; however, after finishing the task, participants were debriefed that the study was about response movements of people who tend to cheat when doing so serves self-interest and where there is no risk of being caught.

Following the instructions, participants saw a page that asked them to make their prediction and preferably write it down on a piece of paper so that they will not forget. This page was repeated before each coin flip. After making the prediction, they were directed to a page where they clicked on a "Flip" button to see an animated coin flip. Once the coin landed, they could go to the next page and report the accuracy of their prediction. On this page, they saw two boxes on the top left and top right of the screen labeled as "Correct" and "Wrong." The assignment of labels to left or right side of the screen was counterbalanced between subjects. Participants were told to click on one of the boxes based on the accuracy of their prediction. If they chose "Correct," they would see a message indicating that they had received a bonus. On the other hand, if they chose "Wrong" they would see a message indicating that they had received no extra bonus. It is worth noting that this procedure assures subjects that there is absolutely no risk of being caught cheating, as their predictions are private and experimenters would never know their actual predictions.[4] Thus, the design of the experiment leaves no place for fear of dishonesty or social embarrassment. Figure 1 illustrates the sequence of events in the task.

Each participant got 20 trials through which the coin outcome was determined using a randomized list. This list was made by a random number generator to guarantee randomness, with the stipulation that heads and tails appeared an equal number of times (50 % probability of heads/tails throughout), for each subject. Following the last trial, participants were prompted to describe any patterns they might have noticed in the sequence of flips. At the end, every participant received the same bonus payment ($0.25 total). All the mouse movements, where participants clicked on "Correct" or "Wrong" to report their accuracy, were recorded for further analysis.

Results

Since participants' predictions were private, we detected lying by comparing the distribution of self-reported accuracy with the expected distribution of fair coin flips. Consistent with previous studies in the field (Greene and Paxton 2009; Shalvi et al. 2012), the distribution of reported correct predictions in the current study ($M = 11.78$, $SD = 2.7$) significantly differs from a fair distribution of random coin flips ($M = 10$), $t(96) = 6.42$, $p < .001$. This suggests that people have actually exhibited dishonest behavior. Figure 2 shows the distribution of self-reported accuracy for Experiment 1. Obviously, researchers cannot tell whether individuals did or did not lie. However, by the logic of this self-serving task, dishonest responses are more likely among participants in the rightmost portion of the histogram than on the left.

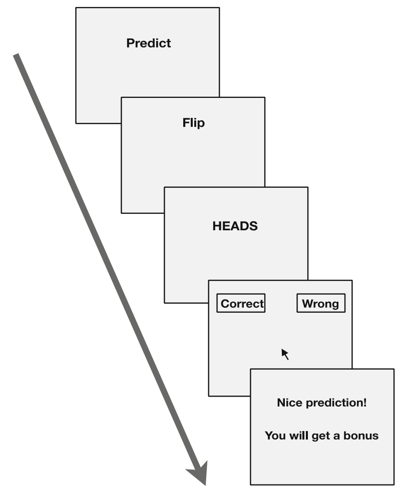

Fig. 1 Task sequence: Subjects (1) make a prediction, (2) flip the virtual coin, (3) see the outcome and (4) evaluate their prediction by clicking on one of the two *boxes* on *top* of the screen (i.e., Correct and Wrong) which were assigned to *left* or *right* on a counterbalanced order. (5) They will be informed that they got a bonus (or not) if they report Correct (or Wrong)

Mouse-trajectory shape

Trials with motion times greater than 5000 ms were removed as outliers (19 out of 1960 trials, approximately 1 % of the data). For the sake of visualizing behavioral patterns in mouse movements, participants were labeled as "Dishonest" (more than 70 % Correct) and "Honest" (<55 % Correct). The higher cutoff (70 %) was chosen based on a one-tailed binomial distribution of individual level dishonesty. Participants with 14 or more (≥70 %) correct predictions out of 20 trials ($M = 15.52$, $p < .05$) were labeled as "Dishonest." In terms of the lower cutoff (55 %), we were aiming to include the greatest number of participants who were not significantly cheating ($M = 9.45$, $p > .05$). The 55 % cutoff gave us the chance to include as many trials as possible that showed no evidence of dishonesty. The mouse trajectories of "Honest"

[4] In order to maximize the feeling of anonymity, which is critical for inducing natural and unrestricted temptation to cheat, we did not ask participants for any personal information. Because we did not have prior research questions involving demographics, we did not collect any data of the sort. It is, however, worth noting that the demographics of MTurk were relatively well known (Mason and Watts 2009; Ipeirotis 2010; Suri and Watts 2011; Mason and Suri 2012).

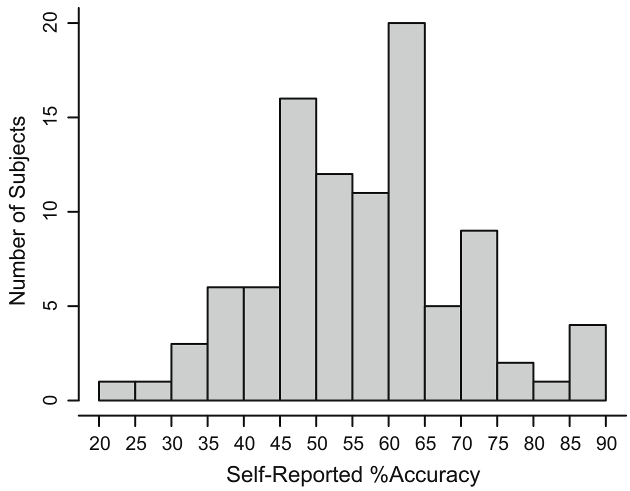

Fig. 2 Distribution of percentage of self-reported correct predictions, in Experiment 1

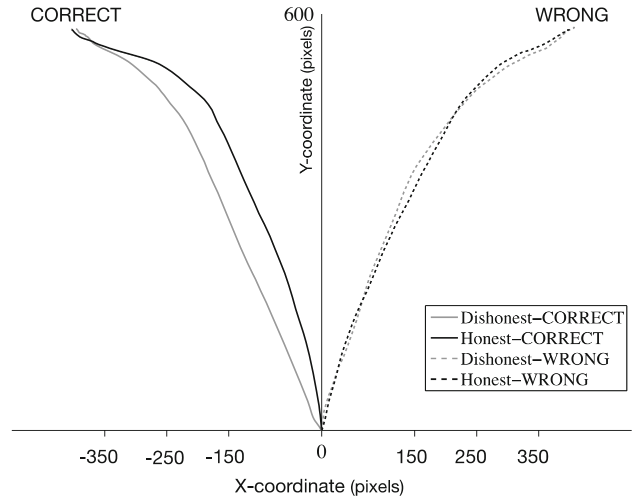

Fig. 3 Average trajectories of "Honest" versus "Dishonest" subjects while choosing Correct (*solid line*) or Wrong (*dashed line*) in Experiment 1

and "Dishonest" participants were interpolated to 101 time steps (see Spivey et al. 2005) and superimposed to produce average trajectories, which are depicted in Fig. 3. The average mouse trajectories of "Honest" participants (in black) and "Dishonest" participants (in gray) show more division while reporting "Correct" (solid) versus "Wrong" (dashed). As shown in Fig. 3, the average trajectory for "Dishonest" subjects when choosing Correct is shorter and more direct compared with "Honest" subjects, suggesting that on average they experienced less hesitation while choosing the deceptive answer. It is important to note that this classification was done merely for demonstration purposes and will not be the basis of data analyses in the following sections. Rather, we include data from all participants in conducting the tests and mixed-effects models.

Mouse-trajectory properties

Mouse-movement trajectories allow a wide variety of dependent variables that can simply be extracted through analysis of the (x, y) coordinates across time. Even though we analyze each independently, they are not interpreted independently: The measures should point to similar patterns regarding cognitive processes. Put differently, this allows us to "triangulate" from many variables the effects on cognitive processing in decisions that are likely to be dishonest versus more honest performances. Below are the definitions of eight variables that have been computed and used to characterize the temporal and trajectory behavior for each trial.

Temporal measures The overall time of one trial from the moment a subject sees the page containing two choices (Correct, Wrong) to the moment they click on one of the two is denoted as *total time* (msec). Moreover, *latency* (msec) is the amount of time that the mouse cursor stays in a region with 80-pixel radius from the initiation point. The region is defined as a latency region, reflecting the time period before participants have initiated their decision. *Motion time* (msec) was calculated as the amount of time after the cursor leaves the latency region until the participant clicks on the final answer (Correct or Wrong).

Trajectory measures *Distance* (pixels) is the Euclidean distance traveled by the trajectory from the initiation point until clicking on the final answer (Correct or Wrong). *Distance in motion* (pixels) is the Euclidean distance traveled by the trajectory after leaving the latency region until clicking on the final answer (Correct or Wrong). *x-flips*, a measure of complexity, are the number of times the mouse cursor changes direction along the *x*-axis (i.e., the axis of decision). *x-range* is defined as the absolute difference between the smallest and largest *x*-coordinates that the mouse reached in transitioning toward the chosen answer. This measure can capture the pull toward the alternative response (relative amount of attraction). Finally, *x-range in motion* is the same concept as *x*-range but calculated merely in the motion time.

The mean value and standard deviation for each variable for Correct and Wrong trajectories are provided in Table 1. It is immediately evident in almost all measures that Correct responses by "Dishonest" subjects tend to show more facilitation compared with Correct responses provided by "Honest" participants: faster times, shorter trajectory distances, simpler trajectories.

We conducted a linear mixed-effects model with a fully specified random effects structure for each of the eight dependent variables. As fixed effects, we used total accuracy,

Table 1 Means and SD of the mouse-trajectory variables by honesty and response type Experiment 1

Variable	Dishonest				Honest			
	Correct		Wrong		Correct		Wrong	
	M	SD	*M*	SD	*M*	SD	*M*	SD
Total time (ms)	1175.31	584.50	1165.76	641.70	1183.82	495.10	1268.44	630.70
Motion time (ms)	909.00	444.29	919.02	529.50	938.86	425.60	1004.58	542.45
Distance (pixels)	879.24	280.00	870.17	203.50	1012.16	537.90	915.71	342.30
Distance in mot.	739.90	275.63	720.03	219.00	866.35	544.24	776.3	348.18
x-range	462.97	132.37	467.66	110.35	510.65	192.01	472.33	142.34
x-range in mot.	401.02	161.28	407.21	140.53	458.22	221.80	419.15	169.68
x-flips	0.95	0.97	0.98	0.97	1.30	1.31	1.15	1.21

Table 2 Coefficient estimates from mixed-effects models predicting variables in Experiment 1

Variable	Total accuracy			Response type			Interaction		
	Coeff.	SE	*t* value	Coeff.	SE	*t* value	Coeff.	SE	*t* value
Total time (ms)	−1.92	13.75	−0.14	−60.09	24.63	−2.43*	1.18	10.77	0.10
Motion time (ms)	−3.23	10.91	−0.30	−52.16	21.82	12.39*	−0.45	9.23	−0.05
Distance (pixels)	−15.84	5.49	−2.9**	32.30	25.68	1.26	−16.98	9.39	−1.80
Distance in motion (pixels)	−13.88	5.58	−2.48*	25.91	25.81	1.00	−13.07	9.71	−1.34
x-range	−5.12	2.32	−2.2*	11.48	10.23	1.12	−8.86	3.66	−2.42*
x-range in motion	−6.64	2.66	−2.5*	9.36	12.44	0.75	−8.47	4.66	−1.81
x-flips	−0.04	0.02	−2.4*	0.001	0.06	0.02	−0.01	0.02	−0.85

* $p < .05$; ** $p < .01$

response type (Correct vs. Wrong) and the interaction term between them. As random effects, we had intercepts for subjects, as well as by-subject random slopes for the fixed effects. A summary of results is provided in Table 2.

In conducting the linear mixed-effects models, we include data from all participants and study the influence of changes in total accuracy on any of the variables. The model indicated that total time is significantly predicted by response type ($B = -60.0$, $p = .014$). The model suggests that a trial reported as correct will be about 60 ms faster than a trial reported as incorrect. Neither the total accuracy nor the interaction term was significant. The results held the same pattern for motion time, as the response type was a significant predictor ($B = -52.1$, $p = .016$).

The analysis revealed that total accuracy had a significant effect on distance ($B = -15.8$, $p = .003$). That is, the total distance along the trajectory was shorter for people with a higher percent correct. This suggests that participants who are more likely to be dishonest had shorter and more direct trajectories indicating less hesitation and more confidence. Similarly, total accuracy had a significant effect on distance in motion ($B = -13.8$, $p = .012$).

In the case of *x*-flips (using Poisson distribution), total accuracy also had a significant effect ($B = -0.04$, $p = .016$), suggesting that number of *x*-flips was slightly lower in participants who are more likely to be dishonest. Thus, changes in direction of mouse movements happened less often in trials that were potentially deceptive, indicating that the participant had more confidence while making that decision. We conducted the same model on *x*-range and *x*-range in motion. The analysis showed that total accuracy was also a significant predictor of *x*-range ($B = -5.1$, $p = .027$) and *x*-range in motion ($B = -6.64$, $p = .012$). This shows that more dishonest subjects illustrated more direct and less curved trajectories. Moreover, we obtained a significant interaction between the total accuracy and response type in predicting *x*-range. The interaction between subjects' total accuracy and whether Correct was reported as the outcome of the trial provided a significant effect on *x*-range ($B = -8.8$, $p = .015$). Thus, consistent with average trajectories (Fig. 3) "Dishonest" participants showed less deviation toward the truthful alternative while choosing the deceptive answer.

In general, the results indicate that participants with higher number of correct responses, and therefore more likely to be dishonest, had more direct trajectories when they were answering correctly. Curiously, more honest participants who reported many incorrect guesses showed the reverse pattern—these subjects had more curved trajectories (higher *x*-range), which illustrates more hesitation. Figure 4 demonstrates the changes in average *x-range* and average *distance* as the total accuracy increases.

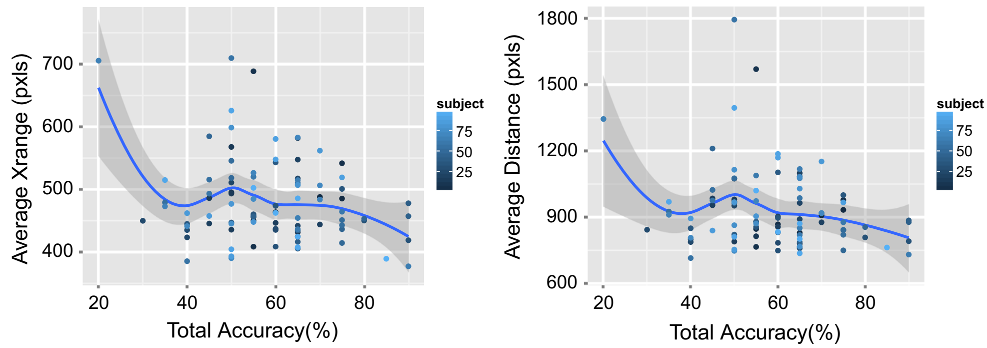

Fig. 4 Average *x-range* decreases in subjects with higher percent correct (*left*). The average *distance* also drops as the total accuracy increases (*right*)

Experiment 2

In the current study, we introduced a task in which participants are not explicitly asked to act dishonestly. Rather, the task tempts them to cheat by offering a bonus payment, under the impression that they are detecting a pattern in the coin flips. In a follow-up experiment, we wished to assess whether offering extra bonus does indeed induce temptation and cause the observed effects. We used the same setup as Experiment 1, only without rewarding participants with a bonus for their accuracy.

Method

In this experiment, participants were asked to report their accuracy after each coin flip and whether they noticed any pattern in the sequence of heads and tails overall. We expected the effects from the previous experiment to be diminished to some extent.

Participants and procedure

Ninety-five subjects were recruited through AMT. The procedure was the same as Experiment 1, except no bonus was given. Participants were led to believe that the main objective of the study was to assess whether implicit learning of underlying patterns is possible through the process of guessing privately and receiving feedback.

Results

The number of "Dishonest" participants (who claimed more than 70 % Correct) was smaller compared with Experiment 1 (9 vs. 16) as well as the maximum self-reported accuracy (85 vs. 90 %). Nevertheless, this distribution was still significantly different from a fair distribution of coin flips [$t(94) = 5.04$, $p < .001$]. This bias could be caused by people's desire to show successful performance in the task and learning the underlying patterns. Lying for reasons other than monetary incentive is not an unfamiliar concept in deception research; Fischbacher and Föllmi-Heusi (2013) report that 20 % of their subjects tend to cheat yet do not maximize their payoff. They refer to this behavior as "partial lying" and show that it is influenced by, but is not necessarily eradicated by, changes in reward structure or risk level. Thus, as expected, the distribution did not show a significant difference from Experiment 1 in regard to self-reported accuracy, χ^2 (1, $N = 95$) = 0.0098, $p = .92$. Figure 5 shows the distribution of percentage correct reported by all 95 subjects.

Mouse-trajectory shape

Figure 6 shows the average trajectories of "Honest" subjects compared with "Dishonest" subjects. It appears that, indeed, incentive was partly driving the cognitive facilitation, as there seems to be less difference between the "Honest" and "Dishonest" average trajectories while choosing Correct.

Mouse-trajectory properties

Trials with motion times greater than 5000 ms were discarded prior to analysis (0.4 %). Mean values and standard deviations for all dependent variables in Correct and Wrong trajectories are listed in Table 3.

The same linear mixed-effects model with total accuracy and response type as fixed effects was used to analyze the data from the second experiment. Total accuracy and the response type (Correct, Wrong) did not have any significant effect on total time or motion time. Similarly, we did not find any significant effect on *x*-range, *x*-range in motion, *x*-flips, distance or distance in motion. Detailed results are provided in Table 4. These results suggest that the effects from Experiment 1 are less prominent after discarding the reward and therefore the temptation to lie. As expected, a tangible reward may encourage the participants to see this as a self-serving opportunity.

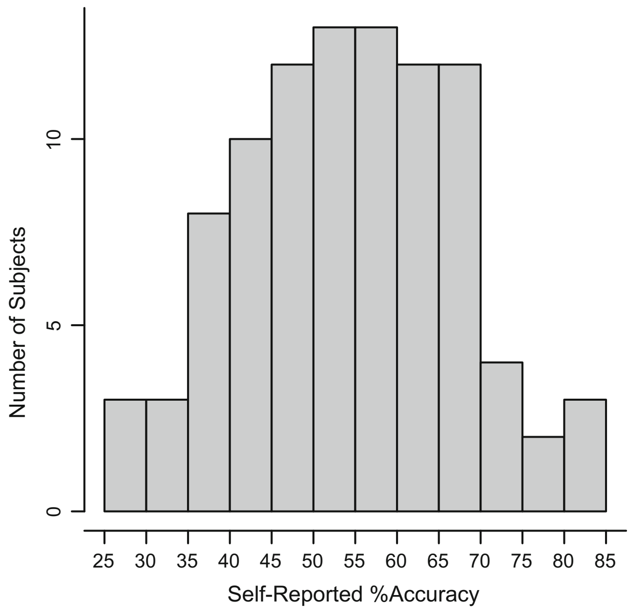

Fig. 5 Distribution of percentage of self-reported correct predictions, in Experiment 2

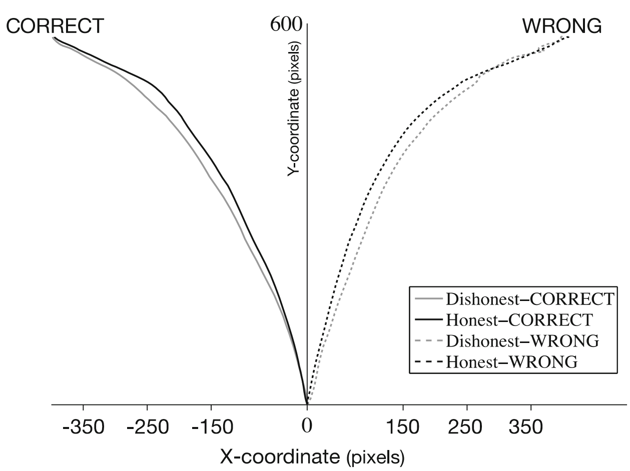

Fig. 6 Average trajectories of "Honest" versus "Dishonest" subjects while choosing Correct (*solid line*) or Wrong (*dashed line*) in non-incentivized condition

General discussion

In this study, we used a novel paradigm to test two competing theories concerning cognitive processes underlying dishonesty. Participants were put in a tempting situation where they could cheat to earn money. They reported the accuracy of their prediction by moving their mouse cursor to the top right or top left of their screen (labeled as Correct or Wrong). The goal was to track participants' mouse movements while they moved to options that could be chosen either truthfully or by cheating. As mouse trajectories are shown to be representative of underlying cognitive processes in decision making (see Spivey and Dale 2006; Song and Nakayama 2008; Freeman et al. 2011), we expected honest and dishonest decisions to demonstrate significantly different shapes. Assuming that honesty is the grounded process, as predicted by the first theory (Gilbert 1991; Duran et al. 2010; Duran and Dale 2012; McKinstry et al. 2008; Spence et al. 2001), it should happen spontaneously with less hesitation and in a shorter timespan, resulting in more direct mouse trajectories. On the other hand, if lying to serve self-interest is the more facilitated process (Greene and Paxton 2009) involving an "automatic tendency" (Shalvi et al. 2012), as stated by the second theory, we expect dishonest decisions to be executed more rapidly with greater confidence and less effort, resulting in shorter and less curved mouse trajectories.

Our findings appear to support the second "automatic tendency" theory. People show less complexity in their mouse movements when they are being dishonest in incentivized tasks. "Dishonest" participants' movements were shorter and more direct with no significant signs of hesitation and less deviation toward the alternative response. "Honest" participants, on the other hand, demonstrated hesitation with longer trajectories and more attempts to change the direction of their mouse cursor. Our results thus suggest that cognitive processes can indeed be facilitated during dishonest decisions when motivation/self-interest is a key task variable. Nevertheless, it is not easy to disentangle the different task variables producing the effects. Variables other than monetary benefit, such as the degree of anonymity on Amazon's Mechanical Turk versus laboratory-based studies, could be responsible for some of the variability reported here and should be explored in future studies. Another factor to consider is that even though the participants were promised a bonus after each correct prediction, they did not know the exact amount. This was intentionally kept simple to provide the minimal conditions for incentivization. Nevertheless, knowing exactly how much dishonesty "pays off" might change the dishonesty rate and response dynamics in interesting ways. The future studies could manipulate the risk level and payment structure in a systematic way.

Lastly, a feature that distinguishes the two theories is the task setup in which each tends to be situated. The second theory is often invoked in tasks where the dishonest response is known in advance and serves the interests of the participant. The first theory is often supported in tasks involving prompted deception where self-serving dishonest decisions are unlikely to be present. This distinction is evident here and with other studies tracking the real-time cognitive processes of deception. For example, the current study is aligned with a situation where participants are tempted to lie, and facilitation for deception is indeed found (Shalvi et al. 2012). In other studies using a prompted setup, the opposite effects occur (e.g., Duran et al. 2010). Rather than

Table 3 Means and SD of the mouse-trajectory variables by honesty and response type in Experiment 2

Variable	Dishonest				Honest			
	Correct		Wrong		Correct		Wrong	
	M	SD	*M*	SD	*M*	SD	*M*	SD
Total time (ms)	1062.3	506.22	1102.75	595.38	1075.27	501.11	1065.10	517.33
Motion time	795.26	358.58	824.54	423.35	852.38	399.55	848.26	422.70
Distance	893.37	313.83	963.40	388.83	922.17	381.27	962.33	361.73
Distance in mot.	743.66	314.38	814.85	402.81	783.22	381.93	825.72	366.53
x-range	466.43	130.83	487.52	141.46	475.02	156.25	509.40	169.25
x-range in mot.	410.11	158.15	432.56	176.67	425.87	182.98	460.87	197.75
x-flips	1.19	1.27	1.5	1.36	1.02	1.13	1.06	1.05

Table 4 Coefficient estimates from mixed-effects models predicting variables in Experiment 2

Variable	Total accuracy			Response type			Interaction		
	Coeff.	SE	*t* value	Coeff.	SE	*t* value	Coeff.	SE	*t* value
Total time (ms)	12.14	11.77	1.03	−1.62	20.97	−0.08	1.40	8.83	0.15
Motion time (ms)	4.4	8.11	0.54	−2.3	17.83	−0.12	2.19	7.43	0.29
Distance (pixels)	−4.85	5.71	−0.85	−20.75	20.17	−1.03	−2.21	9.33	−0.23
Distance in motion	−6.62	5.65	−1.17	−22.40	20.24	−1.11	−2.10	9.37	−0.22
x-range	−3.13	2.45	−1.27	−16.77	10.19	−1.64	1.44	4.28	0.33
x-range in motion	−3.66	2.98	−1.23	−19.26	12.40	−1.55	1.87	5.13	0.36
x-flips	0.02	0.01	1.24	−0.02	0.06	−0.40	−0.03	0.02	−1.20

* $p < .05$; ** $p < .01$

appealing to separate (and competing) cognitive mechanisms to explain these results, a dynamical system approach suggests a more integrative, task-independent interpretation (e.g., Dale and Duran 2013). The behavior observed from both honest and deceptive participants in either task setup can be viewed as a parallel competition between alternative choices that are "fighting" to dictate the final output process (McKinstry et al. 2008).

Thus, there may not be an inevitable sequential order to honesty and dishonesty, where one process is always the preliminary tendency, being occasionally blocked by the other. Rather, we suggest the possibility of a continuous parallel competition between the two options, which can favor any of the two, given the circumstance and the nature of the task. Such possibilities are extremely difficult to ascertain with more traditional measures, which collapse this competition to an end point motor response, or must be inferred from spatial patterns of neural activity. But in the approach used here, where cognition and action are considered to be tightly intertwined, hidden processes of deception and truth may be brought to light.

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References

Abe N, Greene JD (2014) Response to anticipated reward in the nucleus accumbens predicts behavior in an independent test of honesty. J Neurosci 34:10564–10572

Barnes CM, Schaubroeck J, Huth M, Ghumman S (2011) Lack of sleep and unethical conduct. Organ Behav Hum Decis Process 115:169–180

Dale R, Duran ND (2013) Dealing with complexity differently: from interaction-dominant dynamics to theoretical plurality. Ecol Psychol 25(3):248–255

DePaulo BM, Kashy DA (1998) Everyday lies in close and casual relationships. J Pers Soc Psychol 74(1):63

DePaulo BM, Kashy DA, Kirkendol SE, Wyer MM, Epstein JA (1996) Lying in everyday life. J Pers Soc Psychol 70(5):979

Duran ND, Dale R (2012) Increased vigilance in monitoring others' mental states during deception. In: Miyake N, Peebles D, Cooper RP (eds) Proceedings of the 34th annual conference of the cognitive science society. Cognitive Science Society, Austin, pp 1518–1523

Duran ND, Dale R, McNamara DS (2010) The action dynamics of overcoming the truth. Psychon Bull Rev 17:486–491

Fischbacher U, Föllmi-Heusi F (2013) Lies in disguise—an experimental study on cheating. J Eur Econ Assoc 11(3):525–547

Freeman JB, Ambady N (2009) Motions of the hand expose the partial and parallel activation of stereotypes. Psychol Sci 20:1183–1188

Freeman JB, Dale R, Farmer TA (2011) Hand in motion reveals mind in motion. Front Psychol 2:59

Gilbert DT (1991) How mental systems believe. Am Psychol 46:107–119

Gino F, Schweitzer ME, Mead NL, Ariely D (2011) Unable to resist temptation: how self-control depletion promotes unethical behavior. Organ Behav Hum Decis Process 115:191–203

Greene JD, Paxton JM (2009) Patterns of neural activity associated with honest and dishonest moral decisions. Proc Natl Acad Sci USA 106:12506–12511

Gunia BC, Wang L, Huang L, Wang J, Murnighan JK (2012) Contemplation and conversation: subtle Influences on moral decision making. Acad Manag J 55:13–33

Ipeirotis PG (2010) Demographics of Mechanical Turk (Tech. Rep. No. CeDER-10 01)

Kahneman D (2011) Thinking, fast and slow. Macmillan

Magnuson JS (2005) Moving hand reveals dynamics of thought. Proc Natl Acad Sci USA 102(29):9995–9996

Mason W, Suri S (2012) Conducting behavioral research on Amazon's Mechanical Turk. Behav Res Methods 44(1):1–23

Mason WA, Watts DJ (2009) Financial incentives and the performance of crowds. In: Proceedings of the ACM SIGKDD workshop on human computation, pp 77–85

McKinstry C, Dale R, Spivey MJ (2008) Action dynamics reveal parallel competition in decision making. Psychol Sci 19:22–24

Mead N, Baumeister RF, Gino F, Schweitzer M, Ariely D (2009) Too tired to tell the truth: self-control resource depletion and dishonesty. J Exp Soc Psychol 45:594–597

Seymour TL (2001) A epic model of the 'guilty knowledge effect': strategic and automatic processes in recognition. Diss Abstr Int Sect B Sci Eng 61(10-B):5591

Seymour TL, Schumacher EH (2009) Electromyographic evidence for response conflict in the exclude recognition task. Cogn Affect Behav Neurosci 9(1):71–82

Shalvi S, Eldar O, Bereby-Meyer Y (2012) Honesty requires time (and lack of justifications). Psychol Sci 23:1264–1270

Song JH, Nakayama K (2008) Target selection in visual search as revealed by movement trajectories. Vision Res 48(7):853–861

Spence SA, Farrow TF, Herford AE, Wilkinson ID, Zheng Y, Woodruff PW (2001) Behavioural and functional anatomical correlates of deception in humans. NeuroReport 12:2849–2853

Spivey MJ, Dale R (2006) Continuous dynamics in real-time cognition. Curr Dir Psychol Sci 15:207–211

Spivey MJ, Grosjean M, Knoblich G (2005) Continuous attraction toward phonological competitors. Proc Natl Acad Sci 102:10393–10398

Suri S, Watts DJ (2011) Cooperation and contagion in web-based, networked public goods experiments. PLoS One 6(3):e16836

Verschuere B, De Houwer J (2011) Detecting concealed information in less than a second: response-latency based measures. In: Verschuere B, Ben-Shakhar G, Meijer E (eds) Memory detection. Cambridge University Press, London

Vrij A, Mann SA, Fisher RP, Leal S, Milne R, Bull R (2008) Increasing cognitive load to facilitate lie detection: the benefit of recalling an event in reverse order. Law Hum Behav 32(3):253

Walczyk JJ, Roper KS, Seemann E, Humphrey AM (2003) Cognitive mechanisms underlying lying to questions: response time as a cue to deception. Appl Cogn Psychol 17:755–774