Is the bad apple or the bad basket to be blamed? Distinguishing the role of rational self-interest and conformity during the contagion of dishonesty

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Abstract

Learning from others' dishonesty usually involves various motivations, such as the desire to pursue self-interest and the tendency to conform to a dishonest group norm. However, these different processes have rarely been dissociated, which impedes our understanding of how an individual dishonest act propagates and becomes popular in a community. We built a comprehensive model based on the framework of reinforcement learning (RL) to depict both the processes of rational self-interest propensity and dishonesty conformity and examined their roles when people learn to act dishonestly. With an agent-based simulation and empirical studies of samples of diverse cultural backgrounds, we found that rational self-interest propensity was the primary factor driving the propagation of dishonest behaviors, whereas the effect of dishonesty conformity was conditional and context dependent. With an fMRI experiment, we found that the brain implemented dishonesty conformity distinctively when it served different goals. In addition, these two processes of dishonesty were encoded by various functional network architectures. In the background of the COVID-19 pandemic, where public coordination is in high demand but at the cost of self-interest, we found that these two processes of dishonesty exerted discrepant effects on residents' attitudes toward local epidemic control and impacted the prevalence of pathogens unevenly.

[Keywords] rational self-interest; conformity; reinforcement learning; dishonesty; competition; fMRI; dynamic causal modeling; COVID-19

1 **Introduction**

2 Dishonesty is prevalent in our daily lives. It can happen when one's self-interest
3 is compromised, leading to heavy burdens for our society. The detrimental effect of
4 dishonesty is evident not only in the field of economics (Buccioli & Montinari, 2019;
5 DePaulo et al., 1996; Mazar & Ariely, 2006; Serota et al., 2010; Soraperra et al.,
6 2019; Speer et al., 2020) but also in other fields like academia (Harvey, 2020; Wilson,
7 2020). According to the estimate of a recent meta-analysis, 2.9% of researchers are
8 involved in at least one type of research misconduct, and 12.5% have adopted one or
9 more questionable research practices (Xie et al., 2021). Compared to the ample
10 research and sound literature on how dishonest decisions are made individually
11 (DePaulo et al., 1996; Gino & Wiltermuth, 2014; Gneezy, 2005; Kashy & DePaulo,
12 1996; Mazar et al., 2008; for reviews, Abeler et al., 2019; Bazerman & Gino, 2012;
13 Cappelen et al., 2013; Hilbig, 2022; Jacobsen et al., 2018; Stephens, 2017), studies of
14 how social learning influences the emergence of dishonesty are relatively limited.

16 **Learning from others' dishonesty**

17 Social learning is a prominent factor for social decisions (Bandura & Walters,
18 1977), such as the decision to cooperate (Fischbacher et al., 2001, Frey & Meier,
19 2004; Shang & Croson, 2009), the allocation of resources between oneself and others
20 (Krupka & Weber, 2009), and even decisions on moral dilemmas (Brunner &
21 Ostermaier, 2019). A strand of studies has proposed that dishonest behaviors are
22 contagious; that is, people learn from normative cues derived from the environment to

act dishonestly. Such observations were revealed across a wide variety of contexts, including academic cheating, dishonesty in workplace and consuming behaviors in the market (Bicchieri et al., 2018; Buccioli & Montinari, 2019; Brunner & Ostermaier, 2019; Carrell et al., 2015; Chan et al., 2021; Diekmann et al., 2015; Dimant, 2019; Emmett et al., 2019; Fosgaard et al., 2013; Gino et al., 2009; Gulino & Masera, 2019; Kroher & Wolbring, 2015; Innes & Mitra, 2013; Sasaki et al., 2019; Rauhut, 2013). During such a course, processes driven by various motivations, such as the inclination to pursue self-interest and the tendency to conform to group norms, are usually intertwined. However, these processes have rarely been dissociated, which is also probably why inconsistent effects of dishonesty contagion are reported in previous studies (Diekmann et al., 2015; Le Maux et al., 2021; Rauhut, 2013).

To distinguish the different processes driven by various motivations during the contagion of dishonesty, we propose a comprehensive model of decision making that comprises both rational self-interest propensity and dishonesty conformity. Rational self-interest propensity refers to the preference for self-interest and the tendency to realize self-interest rationally (Fiedler et al., 2013; Van Lang et al., 1997). It has been assumed to be an individual disposition that involves actions and attitudes of self-interest calculation (Koning et al., 2010; Meglino & Korsgaard, 2004; Steinel, 2015). During the contagion of dishonesty, such a motivation is largely encouraged since people can utilize the ambiguity of the given context and justify their own misbehaviors with the belief that others also lie (Bicchieri & Xiao, 2009; Bicchieri et al., 2018; Innes & Mitra, 2013; Shalvi et al., 2015). Dishonesty conformity, on the

other hand, is denoted as the tendency to keep aligned with group norms while upholding the truth. Such conformity-driven behaviors are closely related to interpersonal trust (Egebark & Ekström, 2017; Shaleva, 2019; Zafar, 2011) and group affiliation (Cremene & Cremene, 2021; Dimant, 2015; Gino et al., 2009; Rauhut, 2013; Stephens, 2017; Irwin & Simpson, et al., 2013). During the contagion of dishonesty, we suggest that rational self-interest propensity is the primary factor for dishonest behaviors driven by self-interests, while the effect of dishonesty conformity might be modulated by the environment that one encounters and one's own innate inclination to pursue self-interests.

The neural networks underlying dishonesty contagion

One of the most influential arguments made in studies of dishonesty concerns whether dishonest behaviors are performed out of an automatic will (the will theory) or require extra effort to overwrite the honest mode and lie for self-interests (the race theory; Greene & Paxton, 2009). Both of these theories predict increased activation in the network of cognitive control during dishonest decisions, either due to the inhibition of impulses to lie for benefits or to the increased cognitive efforts required to calculate costs and gains and therefore to pursue self-interest rationally (Greene & Paxton, 2009; Speer et al., 2020). The prediction was evident in the findings of a large body of neuroimaging studies that revealed the neural correlates of dishonest behaviors: regions of the frontoparietal networks, such as the dorsal anterior cingulate cortex (dACC), inferior frontal gyrus (IFG), and intraparietal sulcus (IPS),

have been consistently reported to be involved in decisions of cheating or deception (Speer et al., 2020; for meta-analyses, Christ et al., 2009; Lisofsky et al., 2014; for reviews, Greene et al., 2004; Speer et al., 2022). In addition to the cognitive control network, the ventral medial prefrontal cortex has also been frequently reported to be involved in dishonest decisions when valuation and calculation are involved (Pornpattananangkul et al., 2018; Shen et al., 2021; Yin & Weber, 2019). Another line of studies examining deception in social interactions proposed that when people actively infer others' intentions during the course, regions of the Theory of Mind network (e.g., the superior temporal sulcus) were also engaged (Grèzes & Frith, 2004; Lisofsky et al., 2014; Phan et al., 2005; Sip et al., 2010). Despite the numerous efforts made to reveal the neural correlates of dishonest decisions based on people's inner "moral modes" (Speer et al., 2020), how behaviors of social learning in dishonesty are implemented in the brain (e.g., the related activation pattern and interactions between the functional networks) is still largely unknown.

Human beings are social animals who live in groups. With the long evolution of life, our brain shapes us into organisms good at interacting with other creatures, with the superior function of receiving and utilizing social influence efficiently (e.g., the network of theory of mind and mirror neurons, Bekkali et al., 2021; Saxe and Kanwisher, 2003). As the finding of Asch (1951) in his classical line-judgment experiment suggests, people's behaviors are susceptible to opinions of the majority, which happens at a very early stage even before conscious detection, indicating a substantial effect of social influence on decision making (Chen et al., 2012;

89 Shestakova et al., 2013). This 'automatic' feature of social learning might magnify the
90 influence of dishonesty by introducing the concealment and transmission of dishonest
91 behaviors into the community, making them even more difficult to detect and contain
92 (Chan et al., 2021; Dimant & Schulte, 2016). In addition to the theories of social
93 norms and social learning (Bicchieri et al., 2018; Cohn et al., 2014; Cremene &
94 Cremene, 2021; Cremene et al., 2014; Dimant, 2019; Diekmann et al., 2015; Gino et
95 al., 2009; Innes & Mitra, 2013; Irwin & Simpson, 2013; Stephens, 2017), other
96 researchers have proposed that learning from others' dishonesty is instead a self-
97 motivated process involving sophisticated evaluations (Abeler et al., 2019; Bicchieri
98 et al., 2018; Brunner & Ostermaier, 2019; Emett et al., 2019; Maux et al., 2021; Zou,
99 2018). However, evidence from neuroimaging studies that can help settle these
100 arguments is still lacking. To shed light on this gap, we conducted an fMRI
101 experiment in the current study to examine the neural networks and dynamic
102 interactions between the brain networks that underline social learning of dishonesty.

104 **Measurement of spontaneous dishonest behaviors**

105 In the current research, we distinguish the role of rational self-interest propensity
106 and dishonesty conformity in self-interest-driven dishonest behaviors during the
107 contagion of dishonesty. To elicit dishonest behaviors, we employed probabilistic
108 cheating paradigms, which are frequently employed to study dishonest behaviors
109 (Fischbacher U & Föllmi-Heusi F, 2013; Shalvi et al., 2011). In such paradigms,
110 participants are usually instructed to roll a dice or flip a coin several times in private

and report the outcomes that determine their rewards. These tasks offer efficient tools to study spontaneous dishonest behaviors, which were found to be largely impacted by social desirability (Abeler et al., 2019; Jacobsen et al., 2018), and to provide an additional advantage to avoid confounding cognitive demands (Hilbig, 2022). However, since anonymity is fully reserved in such paradigms and lying cannot be detected individually, previous conclusions are usually drawn at the aggregated level (Abeler et al., 2019; Jacobsen et al., 2018). In the current research, we present a novel method combining the comprehensive model and probabilistic cheating paradigm to derive individual parameters of the two processes of dishonesty (e.g., rational self-interest propensity and dishonesty conformity, **Figure 1**) and further examine their related personalities and neural correlates across individuals.

Figure 1: In the current experiments, we employed a coin-flip task to measure spontaneous dishonest behaviors under a context of social learning. Participants were instructed to flip a coin in private five times and were required to report the outcomes of the former four tosses by indicating how many tails they had received. They were told they would be awarded with certain amounts of monetary incentives for each tail they reported. After their reports, participants were provided with feedback about how the previous others had reported on average in the same trial, which was predetermined by the experimenter. We propose a comprehensive model based on the reinforcement learning (RL) framework to estimate the processes of rational self-interest propensity and dishonesty conformity when people learn from others' dishonest behaviors to make their own decisions. Qt_{env} refers to the subjective value that the individuals learned from the environment (i.e., the dishonest group norm; see **Materials and Methods**, equations 1-3). θ refers to the rational self-interest propensity of individuals.

The current research

To distinguish these two processes and their effects during the contagion of dishonesty, we conducted four successive studies using different methods and analyses (**Figure 2**). In **Study 1**, we proposed a model based on the framework of RL to depict the processes driven by rational self-interest and conformity involved when people make dishonest decisions under the influence of a dishonest group norm. The

RL model has been extensively applied to study learning behaviors in both social and nonsocial contexts (Behrens et al., 2008; Liao et al., 2021; Martins et al., 2022; Zhang et al., 2020; for a review, Joiner et al., 2017). We first conducted an agent-based simulation to predict how dishonest reports emerge in communities with various levels of rational self-interest and dishonesty conformity (**Study 1a**). We then verified the model and predictions of the simulation with empirical data and assessed personality traits that were related to these two processes (**Study 1b**). In **Study 2**, we employed experimental manipulations to further dissociate these two processes by including a competitive context and different levels of the predictability of the dishonest group norm. In **Study 3**, we conducted an fMRI experiment to reveal the neural correlate of self-interest-driven dishonest behaviors involved when people learned from a dishonest group norm, and in the final experiment (**Study 4**), we moved forward to examine whether these two processes could be generalized to countries with different cultures and how they impacted a real-life public emergent event (i.e., the COVID-19 pandemic) when self-interest was notably compromised by the need for coordination (e.g., social distancing and quarantine; Perra, 2021). Specifically, we investigated how these two processes affected individuals' responses to epidemic controls during the pathogenic pandemic (COVID-19) and their effects on the progression of the disease at the very beginning of the outbreak.

To anticipate our results, we formally verify that both the processes of rational self-interest and dishonesty conformity exist when individuals learn from others' dishonesty, even though they exert different impacts on the contagion of dishonesty.

170 We found that these two processes of dishonesty were related to various
171 psychological processes (i.e., the preference of value allocation and belief in the
172 predictability of others' behaviors) and could be dissociated and manipulated by
173 reducing the ambiguity of the context of lying or environmental predictability,
174 respectively. Moreover, we found that when the reward rule was uncertain,
175 individuals with high rational self-interest propensities employed the strategy of
176 dishonesty conformity to avoid loss and maximize self-interest, which was mediated
177 by an enhanced process of cognitive control. In addition, individual differences in
178 these two processes were encoded by various functional network architectures of
179 interactions, which were further found to be associated with interpersonal trust and
180 honesty. In a public emergent event where everyone's interest is concerned (the
181 COVID-19 pandemic), rational self-interest propensity predicts an individual's
182 tendency to violate the rule of epidemic control, while dishonesty conformity
183 assembles the common feature of compliance with government regulation and
184 conformity to others' behavior during the pandemic at the country level. We found
185 that these two processes of group dishonesty had distinct effects on the local
186 containment of the disease.

Figure 2: The conceptual outline of the current research. To distinguish the roles of rational self-interest propensity and dishonesty conformity during social learning of others' dishonesty, we proposed a comprehensive model and conducted an agent-based simulation to predict how the behaviors of reports would be impacted by the various levels of the two processes of dishonesty for both the agent and the environment (**Study 1a**). We then validated the model and results of the simulation in a sample with diverse backgrounds (**Study 1b**) and examined the effect of the competitive context and the predictability of the group norm on the two processes (**Study 2**). We also conducted an fMRI experiment to investigate the neural correlates that mediate the interaction of these two processes when the external rule of reward was ambiguous (**Study 3**). In the final experiment (**Study 4**), we conducted a coin-flip task in a cross-cultural sample (22 countries) to examine whether the model could be generalized to countries with various cultures and how these two processes of dishonesty would influence people's attitudes toward epidemic control in the first wave of the COVID-19 pandemic.

Results

The determinant role of rational self-interest propensity in self-interest-driven dishonest behaviors

The comprehensive model. In Study 1, we propose a comprehensive model that combines the processes of rational self-interest propensity and dishonesty conformity to model behaviors of dishonest reports during the contagion of dishonesty. We define the behavior to follow the group norm and make compliant reports instead of reporting the actual outcome as dishonesty conformity. We estimate people's dishonest behaviors under social influence with a two-step method: first, we assume that people learn the dishonest group norm from the external environment and form a posterior belief of others' dishonesty. Based on the Q-learning rule, the belief of others' dishonesty learned from the external environment ($Q_{env(t)}$) is updated according to the discrepancy between the feedback information of peers' reports and the belief in the previous trial ($Q_{env(t-1)}$), which is also termed the prediction error (PE). We then scale the PE with a conformity learning rate (α) reflecting the degree to which the individuals incorporate the feedback information of the dishonest group norm into the action value when they make their own dishonest report. In addition to error-drive learning implemented in classic RL models, we subsequently estimate the process of rational self-interest propensity with a separate and individualized parameter (θ) by adding the parameter to the subjective estimate of the group norm ($Q_{env(t)}$) before it maps to the probability of action, which reflects a procedure of

belief manipulation in a self-serving manner (Bicchieri et al., 2020; Zou, 2018; see **Method** for the formulas). As assumed by the model, the parameter of rational self-interest (θ) adds an overall amount to the action value of report learned from the environment in each trial, which indicates individuals' propensity for rational self-interest while making their own dishonest decisions.

The agent-based simulation. In Study 1a, we conducted an agent-based simulation in a coin-flip task. For each trial, the agents were asked to flip a fair coin five times and report the outcomes they received over the former four tosses. The more tails they reported, the more rewards they earned. Based on the comprehensive model, we simulated the reports of agents with various levels of rational self-interest propensity and dishonesty conformity under the influence of their peers' behaviors, who also varied in these two processes of dishonesty (**Materials and Methods**). The task lasted for seven trials, and we found the agents with higher rational self-interest propensity to report more profitable outcomes throughout the task (average reported frequency of tails: $F(2, 2427)=13131, p<.0001, \eta^2 = .92$, 95% CI: [.87, 1]; **Self $\theta=-1.5$** : $M=0.44$, $SD=0.52$, 95% CI: [0.41, 0.48]; **Self $\theta=0$** : $M=2.32$, $SD=0.50$, 95% CI: [2.28, 2.35]; **Self $\theta=1.5$** : $M=3.93$, $SD=0.20$, 95% CI: [3.92, 3.95], reported frequency of Trial 7: $F(2,2427)=4926, p<.0001, \eta^2 = .80$, 95% CI: [.79, 1]; **Self $\theta=-1.5$** : $M=0.69$, $SD=0.75$, 95% CI: [0.64, 0.74]; **Self $\theta=0$** : $M=2.50$, $SD=0.78$, 95% CI: [2.45, 2.55]; **Self $\theta=1.5$** : $M=3.90$, $SD=0.32$, 95% CI: [3.88, 3.92], **Figure 3a**). In addition, we found a promoting effect of dishonesty conformity on profitable reports when the task ended

(the difference in the reported frequency of tails between Trial 7 and Trial 1:
 $F(2,2427)=44.58, p<.0001, \eta^2=.04, 95\% \text{ CI: } [.02, 1.00]$). However, this effect was
moderated by the rational self-interest of the environment that the agents encountered
($F(2,2427)=19.68, p<.0001, \eta^2=.03, 95\% \text{ CI: } [.02, 1.00]$). We found that the
promoting effect of dishonesty conformity mainly existed in groups encountering an
environment with mild ($F(2,807)=22.2, p<.0001, \eta^2=.05, 95\% \text{ CI: } [.003, 1.00]$) and
intense ($F(2,807)=55.3, p<.0001, \eta^2=.12, 95\% \text{ CI: } [.009, 1.00]$) rational self-interest
but not in the groups where environmental rational self-interest propensity was low
(the neutral condition: $F(2,807)=0.031, p=.97, \eta^2=.00005, 95\% \text{ CI: } [.00, 1.00]$,
Figure 3b). In addition, we found the effect of dishonesty conformity was also
moderated by the rational self-interest of the agents themselves ($F(4,2421)=29.41,$
 $p<.0001, \eta^2=.05, 95\% \text{ CI: } [.03, 1.00]$), that the increasing effect of dishonesty
conformity was more pronounced in those with weak rational self-interest
propensities (Self $\theta=-1.5$: $MD_{self \alpha_{0.5-0.1}} = 0.51, p<.0001, 95\% \text{ CI: } [0.37, 0.66]$,
 $MD_{self \alpha_{0.9-0.5}} = .022, p=.93, 95\% \text{ CI: } [-0.12, 0.17]$, Tukey's HSD adjusted), and that
the effect of dishonesty conformity was reversed in those with strong rational self-
interest propensities (Self $\theta=1.5$: $MD_{self \alpha_{0.5-0.1}} = -.11, p<.0001, 95\% \text{ CI: } [-0.18, -$
 $0.05]$, $MD_{self \alpha_{0.9-0.5}} = -0.0037, p=.99, 95\% \text{ CI: } [-0.068, 0.060]$, Tukey's HSD
adjusted, **Figure 3c**). Regarding the influence of environmental dishonesty
conformity, we found that a higher dishonesty conformity learning rate in the
environment (i.e., peers in the community) would lead to a slight acceleration of the
transmission of the group norm throughout the community (**Figure S2**); however, the

effect did not reach a significant level ($p>.32$). The moderating effects of environmental and self-rational interest propensity on the self-interest-driven dishonest reports above did not differ substantially in communities with various environmental learning rates ($p>0.34$).

In summary, the results of the simulation propose that rational self-interest propensity is the primary factor for dishonest behaviors driven by self-interest, while the effect of dishonesty conformity depends on both the rational self-interest propensity of the environment and that of the agent. To validate these findings, we conducted the ABM with various sets of model parameters (see detailed information in **Supplementary Materials, Figure S3**), and consistent results were found when different parameters were applied.

Figure 3: **a.** The effect of self-rational self-interest propensity on the frequency of profitable outcomes of the last trial (the left column) and the average reported frequency (the right column). **b.** The interaction between self-dishonesty conformity and environmental rational self-interest on the increment of profitable reports. The promoting effect of self-dishonesty conformity on profitable reports was more pronounced when environmental rational self-interest was intense. **c.** The interaction between self-dishonesty conformity and rational self-interest propensity. The effect of self-dishonesty conformity mainly exists when self-rational self-interest propensity is low. We averaged the reports of agents within the condition and present the figure based on the aggregated results for visualization purposes. The midline in the box represents the median, and the top and bottom edges of the box represent the upper (0.75) and lower (0.25) quartiles, respectively. Dots outside the box represent data points that exceed the interquartile (IQR) range of 1.5.

Distinguishing the roles of the two processes of dishonesty in an empirical study

The procedure of the online experiment. To examine whether these two processes both exist during the contagion of dishonesty and verify our proposed comprehensive model, in Study 1b, we recruited a sample with diverse backgrounds through the mTurk platform and conducted a coin-flip task online. We recruited participants to perform the task for seven trials, and in each trial, they were instructed to flip a coin five times and report the frequency of tails they received in the former four tosses, which would determine their rewards (i.e., the participants were told that they would receive 0.1 dollar for each tail they reported). This setup was to elicit dishonest reports since people are more likely to overreport their outcomes by exploiting the last toss without feeling guilty if they received a tail (Shalvi et al., 2011). The experiment involved two phases. In Phase One, the participants were instructed to perform the task without feedback on others' behaviors but were asked to guess how the previous others reported on each trial (see **Materials and Methods** for a detailed description). In Phase Two, the participants were provided with feedback on previous peers' average reports for that trial (which was predetermined), and we evaluated individuals' tendency to conform to the group norm when they made their own report in the subsequent trial. The feedback sequence provided in the task remained the same for all of the participants, which began with three relatively fair trials with averaged reports distributed around an expectancy of 2 (ranging from 1.63 to 2.25), followed by another four unfair trials with reports of approximately 3 and ranging from 2.75 to

3.25. The feedback sequence was predetermined in a pilot study according to the reports of an independent sample (**Materials and Methods**). In addition to the coin-flip task, we measured the participants' preference for value allocation (social value orientation, 9 items, $\alpha = 0.92$, Van Lange & Kuhlman, 1994), interpersonal trust (26 items, $\alpha = 0.94$, Rempel et al., 1985) and honesty personality (honesty-humility of HAXECO personality, 16 items, $\alpha = 0.92$, Lee & Ashton, 2018) at the end of the task to investigate the traits associated with rational self-interest propensity and dishonesty conformity.

Model-free behavioral index. To validate whether the model-derived parameters actually reflect the distinct behavioral tendency, we calculated two model-free indexes to provide face validity to the model-based parameters. We split the trials in Phase Two into two conditions based on the valence of the model-free PE ($PE_t = FB_t - r_t$, r_t denotes participant's own report on trial t); that is, a positive PE condition (PPE), which signals an overreporting of the group norm, and a negative PE condition (NPE), which signals an underreporting of the group norm. We averaged the updates in reports ($RU = r_{t+1} - r_t$) in each condition for each individual. If the participants did not conform to the group norm, the average updates in these two conditions should be equivalent and centered around zero. In contrast, a positive average update in the PPE condition and a negative average update in the NPE condition signal a tendency of conformity to the group norm. We denoted a model-free index of dishonesty conformity (MF- α) as the average update of reports between the conditions of PE ($\frac{RU \text{ in PPE} - RU \text{ in NPE}}{2}$). For

rational self-interest, we denote the report of the first trial in Phase Two as the model-free index, where the behaviors of others were not yet revealed and participants acted on their own inclination to pursue self-interest.

We found that the model-free indexes of rational self-interest and dishonesty conformity were specifically correlated with the model-derived parameters (partial $r_{\alpha, MF-\alpha}=.33, p<.001$; partial $r_{\theta, MF-\theta}=.50, p<.001$; partial $r_{\alpha, MF-\theta}=-.11, p=.035$; partial $r_{\theta, MF-\alpha}=-.042, p=.41$), indicating that the model-based parameters (i.e., rational self-interest propensity θ and dishonesty conformity learning rate α) capture the latent decision processes of rational self-interest and conformity, respectively.

The effect of rational self-interest propensity and dishonesty conformity on self-interest-driven dishonest reports. We found that the parameter of rational self-interest propensity (θ) strongly correlated with the average reported frequency of tails in both phases (Phase One: Spearman's $r=.51, p<.001$; Phase Two: Spearman's $r=.81, p<.001$), indicating its primary role in promoting self-interest-driven dishonest behaviors. Dishonesty conformity learning rate α , on the other hand, was negatively correlated with the average report in both phases (Spearman's $r=-.108, p=.033$; Spearman's $r=-.107, p=.035$). In addition, we found that these two processes interacted to influence the average report when others' reporting behaviors were revealed ($B=-0.45, SE=0.054, t(380)=-8.50, p<.0001$). We found that the promoting effect of dishonesty conformity on the frequency of profitable reports mainly existed in individuals with lower rational self-interest propensity ($B=0.50, SE=0.059,$

$t(380)=8.58, p<.0001$), while the effect was reversed in those with high rational self-interest propensity ($B=-0.22, SE=0.062, t(380)=-3.49, p=.0005$), which is consistent with the findings of the simulation. This suggests that when encountering an environment in which others lie for self-interest to some extent, the enhancing effect on dishonest behaviors driven by self-interests of dishonesty conformity is more salient in those with weaker rational self-interest propensities. For those with stronger rational self-interest propensities, a higher tendency to conform to the group norm acts as a buffer to constrain the deviant behaviors of overclaiming.

Personality traits associated with the two processes of dishonesty. We found that rational self-interest propensity (θ) was associated with individual differences in social value orientation: participants with a proself orientation had a stronger rational self-interest propensity than those with a prosocial orientation ($MD=0.22, SE=0.079, t(386)=2.76, p=.006, 95\% CI: [0.062, 0.37]$, Cohen's $d=.27$), while the tendency toward dishonesty conformity was not significantly different between proself and prosocial individuals ($MD=-0.060, SE=0.039, t(386)=-1.55, p=.12, 95\% CI: [-0.14, 0.02]$, Cohen's $d=-.17$). In contrast, we found that the dishonesty conformity learning rate (α) was correlated with the factor of predictability of the interpersonal trust scale (Spearman's $r=0.13, p=.012$), suggesting that those who believed surrounding others were more predictable are more likely to follow the dishonest group norm when they made their own decisions. To test the robustness of the association, we further performed a bootstrap analysis of the correlation relationship 10,000 times and

obtained a 95% confidence interval of [0.028, 0.226], which excludes zero, revealing a substantial relationship between the conformity learning rate and the belief in predictability. For the honest personality, we found that rational self-interest propensity was negatively correlated with greed avoidance ($r=-0.105$, $p=.039$) and modesty ($r=-0.14$, $p=.005$), while dishonesty conformity was positively correlated with fairness ($r=.10$, $p=.047$) and greed avoidance ($r=.11$, $p=.027$). However, the correlation of dishonesty conformity decreased to a nonsignificant level when the effect of rational self-interest propensity was controlled ($ps>.075$, see [Table S2](#) for the correlation table).

Considering the random effect of the task (i.e., participants might have reported an outcome of four tails because they actually received four tails in the toss exercise), we further verified the above effects by simulating the reporting behaviors in samples with an identical sample size ($N=388$). We generated the simulated reports by sampling from a (random) binomial distribution of a four-time toss and fit the comprehensive model to the simulated behaviors. We then calculated the above correlations as well as the interaction effect between the two processes on dishonest reports. By repeating the analysis 1000 times, we obtained the null distribution of these effects. We found that the empirical effect sizes observed in the current experiment (i.e., the correlation coefficients and η^2) fell outside the 95% CI of the null distributions, suggesting that the findings did not result from randomness ([Figure S7](#)).

Based on the results of our first study, we found that rational self-interest-driven and conformity-driven dishonest behaviors both existed during the contagion of dishonesty. Rational self-interest is the primary factor for the emergence of dishonest behaviors driven by self-interest. In addition, these two processes are related to different personalities, suggesting that they are associated with discrepant psychological processes.

Congruent norms increase dishonesty conformity but restrain rational self-interest propensity in a competitive context

In Study 1b, we found a correlation between dishonesty conformity and belief in the predictability of others. In Study 2, we manipulated the predictability of the group norm and examined whether dishonesty conformity could be influenced by environmental predictability. We manipulated the variance of the feedback sequences to provide group norms with various levels of predictability. In addition, we included a competitive context in which lying caused salient harm to another person's benefit, therefore reducing the ambiguity of the context and chances of self-justification (Shalvi et al., 2011). We hypothesized that the predictability of group norms would specifically impact individuals' tendency toward dishonesty conformity, while the competitive context would mainly exert an effect on people's rational self-interest propensity during the contagion of dishonesty. We recruited 153 participants from the United States through mTurk to participate in the task and assigned them randomly to

428 six conditions based on context (competitive vs. noncompetitive) $\times$ variance of
429 feedback (high vs. moderate vs. low variance, **Materials and Methods**). The results
430 of Study 2 revealed that the dishonest conformity learning rate (α) was significantly
431 correlated with the magnitude of variance of the feedback sequence (Spearman's
432 $r=-.21, p=.009$). That is, when the group norm was more variable and less predictable,
433 the participants conformed less to others' behaviors. Neither a main effect nor an
434 interaction of the context of competition on dishonesty conformity was found
435 ($ps>.19$). Rational self-interest propensity, on the other hand, decreased in the groups
436 under a competitive context ($M_{non-compet}=0.44, SD=0.79, M_{compet}=0.12, SD=0.61,$
437 $t(150.96)=-2.83, p=.005$, Cohen's $d=.45$, 95% CI=[-0.547, -0.097]). An interaction
438 between the variance of the feedback sequence and context on rational self-interest
439 propensity was also found ($F(2,147)=4.06, p=.019, \eta_p^2=.052$), suggesting a decreasing
440 effect of the competitive context on rational self-interest propensity when the group
441 norm was more predictable ($MD=-0.78, SE=0.20, F(1,147)=15.17, p<0.001$, 95% CI:
442 [-1.17, -0.38]). These findings validate the causal relationship between the
443 predictability of group norms and dishonesty conformity; additionally, a competitive
444 context decreases the expression of individuals' rational self-interest propensity when
445 dishonest reports cause salient harm, especially when the group norm is more
446 congruent and predictable.

447

**Enhanced cognitive control mediates the effect of dishonesty
conformity on self-interest-driven dishonest behaviors when rational
self-interest propensity is high.**

In previous studies, the reward rule of the coin-flip task was certain and clear; therefore, for those with stronger rational self-interest propensities, desires to maximize self-interests could be fulfilled by making one's own decisions without paying attention to others' behaviors. In Study 3, we investigate how these two processes of dishonesty interact when the rule of reward is uncertain and how such processes are implemented in the brain.

The dice-rolling task. We modified the coin-flip task to a paradigm of dice rolling, and for each trial, we instructed the participants to choose three dice from four covered ones shown on the screen privately and report the sum of the numbers of dice they chose when the outcomes were revealed ([Figure 4a](#)). We told them they were teamed up with another partner who was randomly sampled from the previous participants. Different from the previous studies, the rule of reward of the current experiment was uncertain: in some of the blocks, the one in the pair reporting a larger sum of points won the game and received a prize, while the other lost and received no reward. For the other blocks, the one that reported a smaller number won. We instructed participants to learn the rule of the block through the feedback of others' averaged reports. They were told that the rules of reward for different blocks remained the same across all participants; however, the rules of game for their previous peers were different: the previous participants learned their outcome of the

game for each trial instead of the information of others' behaviors. Since the participants did not need to report the dice that they chose in advance, they were provided with an opportunity to lie for rewards without being detected. The outcomes of the dice rolling were generated by sampling from a uniform distribution for each dice (**Methods and Materials**). With this setting, those driven by high rational self-interest propensities could adopt a strategy to conform to others' behavior at the initial trials where the rule was unclear to accumulate evidence and avoid loss and then shift to overreporting when the rule was learned (Toelch & Dolan, 2015). Participants performed the dice-rolling task for three blocks (each of which involved 15 trials) with their fMRI BOLD signal scanned (**Methods and Materials**). At the end of the experiment, they were asked to rate how much they thought their previous peers were honest about their reports with a 5-point Likert scale (from 1 "totally dishonest" to 5 "totally honest," which were recoded in the subsequent analysis). Scales of interpersonal trust ($\alpha=0.98$), the honesty-humility dimension of HAXECO ($\alpha=0.87$) and social value orientation ($\alpha=0.98$) were also measured.

The effect of rational self-interest propensity and dishonesty conformity on self-interest-driven dishonest reports. In all three blocks, we found an overall trend of overreporting in line with the rule of the block, indicating that the participants learned from the group norm to overclaim rewards (**Figure S8**, Block 1: *KS* test, $D=0.162$, $p<.001$; Block 2: *KS* test, $D=0.164$, $p<.001$; Block 3: *KS* test, $D=0.161$, $p<.001$). To win rewards, the participants needed to determine the rule of the current block and compete with their assigned partners by reporting more profitable outcomes. Since

feedback from the previous peers provided in the task was more remunerative than the optimal choices available (**Figure S9**), the participants should have reported outcomes beyond the available options to pursue self-interests. We termed such behaviors full lying reports, which provided salient indicators of self-interest-driven dishonest behaviors during the contagion of dishonesty and were also evident in the current observations (**Figure S10-11**). Based on the parameters derived from the comprehensive model (**Materials and Methods**), we found that rational self-interest propensity was positively correlated with the frequency of full-lying reports in all three blocks ($r_s > 0.43$, $p_s < .0023$). However, the correlation between dishonesty conformity and full lying reports was less consistent (Block 1: $r = .15$, $p = .34$; Block 2: $r = .31$, $p = .04$; Block 3: $r = .25$, $p = .09$). In addition, we found that the relationship between dishonesty conformity and full lying reports was moderated by individuals' rational self-interest propensities in the latter blocks (Block 1: $B = .045$, $SE = .036$, $t(40) = 1.26$, $p = .65$; Block 2: $B = .083$, $SE = .02$, $t(43) = 3.55$, $p = .0029$; Block 3: $B = .10$, $SE = .034$, $t(44) = 2.98$, $p = .014$, Bonferroni corrected), where the promoting impact of dishonesty conformity on the propagation of dishonest behaviors mainly existed when rational self-interest propensity was high (Block 2: high θ : $B = .083$, $SE = .015$, $t(43) = 5.44$, $p < .0001$; low θ : $B = .018$, $SE = .012$, $t(43) = 1.51$, $p = .14$; Block 3: high θ : $B = .080$, $SE = .017$, $t(44) = 4.61$, $p < .0001$; low θ : $B = .014$, $SE = .012$, $t(44) = 1.18$, $p = .24$).

Brain activations associated with self-interest-driven dishonest reports in the decision phase. To investigate the neural correlates of self-interest-driven dishonest

reports during the contagion of dishonesty, we implemented two GLMs for the onsets of the report (GLM 1) and feedback (FB) phases (GLM 2). For both GLMs, the onsets of the four experimental phases (i.e., choice, outcome, report and feedback, **Figure 4a**) were included as regressors, and to control the confounding effects of motion and cognitive demands on calculation, in GLM 1, we included the frequency of button pressing and reaction time as modulators of no interest. For GLM 2, a parameter modulator of the feedback phase that denotes the disadvantages of participants' self-report compared to feedback was included to control the effect of loss (**Materials and Methods**). For the group-level analysis, the percentage of full-lying reports of each participant in each block was entered as the covariate and regressed on the beta estimates derived from the first-level GLMs.

The results of GLM 1 revealed that a higher frequency of full-lying reports was associated with more activation in regions distributed in the frontoparietal network, including the dACC, right IFG and right IPS (**Table 1, Figure 4b**). In addition, we found that the activated regions overlapped with the meta-analytical map of cognitive control derived from Neurosynth (<https://neurosynth.org/>), suggesting an enhanced process of cognitive control when the participants decided to make profitable reports beyond the scope of available options (**Figure 4c**). We found that rational self-interest interacted with dishonesty conformity to impact activation in the dACC ($B=0.073$, $SE=0.03$, $t(133)=2.42$, $p=.017$), right IFG ($B=0.10$, $SE=0.034$, $t(133)=3.02$, $p=.003$) and right IPS ($B=0.14$, $SE=0.07$, $t(133)=2.01$, $p=.046$). The result of the simple slope analysis revealed that a higher level of dishonesty conformity was related to more

537 activation in the cognitive control network, but only when self-interest propensity was
538 high (dACC: $B=0.059$, $SE=0.018$, $t(133)=3.27$, $p=.0013$; right IFG: $B=0.083$,
539 $SE=0.021$, $t(133)=3.97$, $p=.0001$; a marginal effect for the right IPS: $B=0.69$, $SE=0.4$,
540 $t(133)=1.71$, $p=.08$); the association vanished when self-interest propensity was low
541 (dACC: $B=0.0056$, $SE=0.013$, $t(133)=0.43$, $p=.67$; right IFG: $B=0.0085$, $SE=0.016$,
542 $t(133)=0.54$, $p=.59$; right IPS: $B=-0.46$, $SE=0.39$, $t(133)=-1.17$, $p=.24$). Moreover, the
543 activations in the cognitive control network also interacted with the rational self-
544 interest propensity to predict full lying report decisions (dACC: $B=0.042$, $SE=0.011$,
545 $t(133)=3.80$, $p=.0002$; right IFG: $B=0.036$, $SE=0.0095$, $t(133)=3.83$, $p=.0002$; right
546 IPS: $B=0.018$, $SE=0.0050$, $t(133)=3.51$, $p=.0006$). We found that more activation in
547 the cognitive control network led to more full lying reports specifically when rational
548 self-interest propensity was high (high θ : dACC: $B=0.052$, $SE=0.0075$, $t(133)=6.93$,
549 $p<.0001$; right IFG: $B=0.048$, $SE=0.007$, $t(133)=6.73$, $p<.0001$; right IPS: $B=0.15$,
550 $SE=0.025$, $t(133)=6.23$, $p<.0001$; low θ : dACC: $B=0.0092$, $SE=0.0089$, $t(133)=1.04$,
551 $p=.3$; right IFG: $B=0.0044$, $SE=0.0089$, $t(133)=0.49$, $p=.62$; right IPS: $B=0.0073$,
552 $SE=0.0093$, $t(133)=0.78$, $p=.44$). We continued to test the mediation effects of
553 activation in the dACC and right IFG separately and found that the activations in
554 these two regions mediated the relationship between dishonesty conformity and
555 decisions of full lying with the moderation of rational self-interest propensity (**Figure**
556 **4d**). The indirect effect mainly existed when rational self-interest was high (for dACC
557 at high θ : $B=0.14$, $SE=0.08$, bootstrapped 95% CI: [0.0092, 0.32], at low θ : $B=-0.01$,
558 $SE=0.017$, bootstrapped 95% CI: [-0.049, 0.021]; for right IFG at high θ : $B=0.20$,

$SE=0.091$, bootstrapped 95% CI: [0.042, 0.41], at low θ : $B=-0.022$, $SE=0.021$, 95% CI: [-0.069, 0.014]). These findings imply that an enhanced process of cognitive control mediated the promoting effect of dishonesty conformity on full lying reports, specifically when rational self-interest was strong. The effect of the right IPS was similar; however, it did not reach a significant level (high θ : $B=0.12$, $SE=0.067$, 95% CI: [-0.010, 0.26], low θ : $B=-0.013$, $SE=0.019$, 95% CI: [-0.058, 0.017]).

Figure 4: a. An illustration of the dice-rolling task of the fMRI experiment. A choice screen of 2 s (with a 0-2 s jitter) was first shown, and the participants were required to select three of the covered dice in private. Then, a screen of the outcome was presented for 4 s with a jitter of 0-2 s. After this, the participants entered a report

screen that instructed them to report the sum of points of their chosen dice within 4 s using a slider bar (ranging from 3 to 18). Then, a feedback screen presented the average report on the sum of points of the 16 previous peers, followed by an intertrial interval (ITI) of 2-6 seconds. **b.** Brain activations related to the frequency of full lying reports, including the right IFG, dACC and right IPS (whole brain: $P < .05$ cluster-wise FDR-corrected for positive activation, cluster-forming threshold $P < .005$). **c.** The overlap between the activated networks and the meta-analytical map of the cognitive control network derived from Neurosynth (plotted in blue). **d.** The mediation model of the effect of the activation of the right IFG (left) and dACC (right) on the relationship between dishonesty conformity and the decision to make full lying reports, moderated by rational self-interest. $*p < .05$, $**p < .01$, $***p < .001$.

Brain activations associated with self-interest-driven dishonest reports in the feedback phase. The results of GLM 2 revealed that when the individuals were more likely to make self-interest-driven dishonest reports, they engaged in stronger activations in the vmPFC and aSTS when they learned of others' dishonest behaviors (**Table 2, Figure 5a**). More importantly, the associations between vmPFC and aSTS and full lying reports were moderated by rational self-interest propensity (vmPFC: $B = 0.025$, $SE = 0.01$, $t(133) = 2.40$, $p = .018$; aSTS: $B = 0.019$, $SE = 0.007$, $t(133) = 2.60$, $p = .010$), and the associations mainly existed when rational self-interest was high (vmPFC: $B = 0.21$, $SE = 0.054$, $t(133) = 4.0$, $p = .0001$; aSTS: $B = 0.17$, $SE = 0.037$, $t(135) = 4.47$, $p < .0001$). Concurrently, activation in the aSTS was positively correlated with participants' ratings of lying for previous peers (Spearman's $r = 0.30$, $p = .036$), and the correlation was also moderated by rational self-interest propensity ($B = -0.15$, $SE = 0.072$, $t(45) = -2.06$, $p = .046$, **Figure 5b**) with a positive association existing only when rational self-interest propensity was low (low θ : $B = 2.14$, $SE = 0.73$, $t(25) = 3.28$, $p = .002$, high θ : $B = 0.16$, $SE = 0.29$, $t(45) = 0.53$, $p = .60$). We further verified the interaction with an ordered logistic model that treats the rating of lying as a discrete

and ordered variable, and consistent results were obtained ($B=-0.37$, $SE=0.16$, $t(45)=-2.28$, $p=.027$). These findings suggest that distinct processes of group norm interpretation and value calculation are involved during self-interest-driven dishonest reports, given the various levels of rational self-interest propensity.

The results of the behavioral analyses and GLMs imply that when the context of a decision was uncertain, dishonesty conformity was utilized as a strategy to maximize self-interest in those with a stronger rational self-interest propensities (see **Supplementary Materials** for additional analyses). When dishonesty conformity serves rational self-interest propensity, increased activation of the cognitive control network mediates such a process, probably resulting from an enhanced process of self-justification when individuals utilize a dishonest group norm to justify their own dishonest behaviors.

Figure 5: **a.** Brain activations related to the frequency of full lying reports in the feedback phase, including the activation of the vmPFC and aSTS regions (whole brain: $P<.05$ cluster-wise FDR-corrected for positive activation, cluster-forming threshold $P<.005$). **b.** The distinct role of aSTS in encoding the belief (rating) of lying in others given individuals' rational self-interest propensity. $*p<.05$, $**p<.01$, $***p<.001$.

Table 1. Brain activations related to the frequency of full-lying reports in the report phase.

Brain regions	k	t value	MNI coordinates		
			x	y	z
Right IFG	2469	6.80	46	20	20
Right MFG		4.80	38	0	52
Right IPS	1045	5.76	38	-58	44
dACC	790	4.79	0	16	38
Left MFG		3.84	-22	-2	40

Note. IFG, inferior frontal gyrus; MFG, middle frontal gyrus; IPS, intraparietal sulcus; dACC, dorsal anterior cingulate cortex (whole brain: $P < 0.05$ cluster-wise FDR-corrected for positive activation, cluster-forming threshold $P < 0.005$).

Table 2. Brain activations related to the frequency of full-lying reports in the feedback phase.

Brain regions	k	t value	MNI coordinates		
			x	y	z
Right SFS	886	3.73	26	24	42
Right MFG		3.50	44	34	38
Left MTG	962	4.60	-54	-48	-4
Left aSTS		4.10	-58	-28	-12
rACC	475	4.15	14	54	-2
vmPFC		3.41	-2	36	-10

Note. SFS, superior frontal sulcus; MFG, middle frontal gyrus; MTG, middle temporal gyrus; aSTS, anterior superior temporal sulcus; rACC, rostral anterior cingulate cortex; vmPFC, ventral medial prefrontal cortex (whole brain: $P < 0.05$ cluster-wise FDR-corrected for positive activation, cluster-forming threshold $P < 0.005$).

Correlation between brain connectivity and the two processes of dishonesty. In

addition to brain activations, we are interested in how these two processes of dishonesty modify the dynamic interactions between the brain regions that are involved in self-interest-driven dishonest decisions. Therefore, we further examined the dynamic interactions that encode these two processes of dishonesty by using the method of dynamic causal modeling (DCM). DCM uses a biophysically motivated and parameterized forward model (i.e., hemodynamic model) to link neuronal activation elicited by experimental stimuli to the observed signals (Friston et al.,

2003; Stephan et al., 2010). We first specify an architecture in which the frontoparietal network identified in GLM 1 is elicited by the action cue of the report screen, whereas aSTS and vmPFC identified by GLM 2 receive inputs of the group norm (Stephan et al., 2010; Harding et al., 2015). We further assume a model structure with a hub region connecting different networks, that is, the network of cognitive control (dACC, IFG and IPS), reward valuation (vmPFC) and theory of mind (aSTS), which have also been revealed in previous studies of dishonest behaviors (Shen et al., 2021). Specifically, we use dACC or vmPFC to serve as the hub connecting aSTS to the completed network given their roles in conflict detection (Harding et al., 2015; Vries et al., 2015; Alexander & Brown, 2010) and value abstraction guided by goals (Cortese et al., 2021; Yin et al., 2019), respectively. We employ a factorized design with a grid search to construct the model space, which is based on the following factors: (1) the region of the hub (dACC vs. vmPFC); (2) the structure of connection between the prefrontal cortex and vmPFC (i.e., the number of nodes of the frontoparietal cortex connected to vmPFC); (3) (reciprocal or) directional interaction between the connected nodes; and (4) nodes that receive driving inputs (i.e., the inputs of action cues for the report phase and the information of group norms for the feedback phase, respectively, **Materials and Methods, Figure 6a**). With family rfx-BMS analysis, the model structure with dACC serving as a hub region ($X_p = 1$, **Figure 6b**), all nodes of the frontoparietal network interacting with vmPFC ($X_p = 1$, **Figure 6c**), reciprocal interactions between brain regions ($X_p = 1$, **Figure 6d**) and a full impact of driving inputs ($X_p = 0.51$, **Table 3**) were identified.

Figure 6: **a.** Model specification for the structure of DCMs. These models fall into families factorized by the region of the hub to connect aSTS to the completed network (dACC: Model 1-7 vs. vmPFC: Model 8-14) and the pattern of connection between nodes of the frontoparietal cortex and vmPFC (1 node: Model 1-3 & Model 8-10 vs. 2 nodes: Model 4-6 & Model 11-13 vs. 3 nodes: Model 7 & Model 14). **b.** The results of family rfx-BMS analysis comparing models with dACC or vmPFC serving as the hub region. **c.** The results of family rfx-BMS analysis for comparing models with one, two or three nodes interacting with vmPFC. **d.** The results of family rfx-BMS analysis for comparing models with reciprocal or directional interaction between regions of dACC, IPS, IFG, aSTS and vmPFC based on the winning family of Stage Two.

687 **Table 3.** DCMs with various driving inputs of Stage Three.

Rank	Driving inputs					Xp
	dACC	IPS	IFG	vmPFC	aSTS	
1	a	f	a	a	f	0.5555
2	a	f	a	a		0.2203
3	a	f		a		0.1557
4		f	a			0.0179
5	a	f			f	0.0154
6		f		a		0.0095
7			a	a	f	0.0065
8		f		a	f	0.0049
9	a	f		a	f	0.0043
10		f	a	a		0.0034
11		f	a		f	0.0023
12			a		f	0.0018
13	a	f				0.001
14				a	f	0.0007
15	a	f	a			0.0003
16	a		a	a	f	0.0002
17		f	a	a	f	0.0002
18	a	f	a		f	0.0001
19	a		a		f	0
20	a			a	f	0
21	a				f	0

688 Note. “a” and “f” indicate the inclusion of a driving input of action cue or feedback of
 689 group norms to the indicated regions, respectively. Xp = exceedance probability.

690

691 To examine which of the dynamic interactions within the completed functional
 692 network architecture encode rational self-interest propensity and dishonesty
 693 conformity, we conducted parametric empirical Bayes (PEB) analysis, which employs
 694 a hierarchical framework of group-level analysis to examine the effect of subject-level
 695 (2nd level) covariates on the parameters of DCM derived from the individual level (1st
 696 level, see **Materials and Methods** for details). With the PEB analysis, we found that
 697 the tendency of dishonesty conformity was related to the interactions of IFG→IPS
 698 (0.30), IPS→IFG (-0.15), vmPFC→dACC (-0.21), vmPFC→IFG (0.25) and
 699 vmPFC→IPS (-0.22, **Figure 7a**). Moreover, we found that the connectivity of

vmPFC→dACC and vmPFC→IPS (averaged across blocks) was also correlated with the belief of predictability across participants (vmPFC→dACC: $r=-.3$, $p=.03$; vmPFC→IPS: $r=-.28$, $p=.05$, **Figure 7d-e**). These effects suggest that for those who hold the belief that others are predictable, their dynamic interactions from vmPFC to dACC and IPS were weakened, which were further associated with an increased tendency toward dishonesty conformity, suggesting that these dynamic interactions might be the neural basis of the relationship between the belief of predictability and dishonesty conformity. Regarding rational self-interest propensity, four different intrinsic connections were identified to contribute to the individual difference in this inclination at the group level (**Figure 7b**), including decreased connectivity of IFG→dACC (-0.016), aSTS→dACC (-0.018), and vmPFC→IFG (-0.019) and increased self-inhibition in vmPFC (0.029) in individuals with stronger rational self-interest propensities. To dissociate processes of dishonesty conformity driven by different motivations, we built another PEB model to examine the connectivity associated with the interaction between the two processes. The results revealed that the connectivity of dACC→dACC (-0.064), dACC→aSTS (0.88), dACC→vmPFC (0.042), aSTS→aSTS (0.11), IFG→IFG (0.066), IFG→vmPFC (-0.029), vmPFC→IFG (-0.15) and vmPFC→IPS (-0.095) was associated with the (mean-centered) interaction term (**Figure 7c**).

We further applied leave-one-out cross validation and used the intrinsic connections to predict the behavioral parameters of the participants (**Materials and Methods**). We found that the connectivity of aSTS→dACC successfully predicted

individual rational self-interest propensity above a chance level ($r=.16$, $p=.029$). In addition, we found that the dynamic interaction from dACC to vmPFC successfully predicted the interaction with the largest effect size (dACC→vmPFC: $r=.25$, $p=.001$, see **Supplementary Materials** for completed results). After extracting the estimates of the winning model (rank 1 of **Table 3, Materials and Methods**), we found that rational self-interest was positively correlated with the connectivity of dACC→vmPFC but only when the tendency toward dishonesty conformity was high (high α : $B=0.013$, $SE=0.006$, $t(133)=2.06$, $p=.041$; low α : $B=-0.003$, $SE=0.004$, $t(133)=-.075$, $p=.45$). In addition, we found that the average connectivity of dACC→vmPFC (across blocks) was stronger in individuals with lower sincerity scores ($r=-.32$, $p=.03$) measured by the honesty-humility subscale of HAXECO (**Figure 7f**), indicating the neural architecture of the dishonest personality.

The DCM results reveal the dynamic circuit that underlines self-interest-driven dishonest reports during the contagion of dishonesty: the dACC region serves as the hub of the network to integrate information of the various operations (e.g., conflict resolution, norm interpretation and valuation), with the two processes of dishonesty implemented differently in the dynamic interactions between the regions.

Figure 7: PEB analysis results for the effective connectivity encoding the processes of dishonesty conformity (a), rational self-interest propensity (b), and the interaction between the two processes (c) with a threshold at strong evidence of 0.99 posterior probability. The correlation between the factor of predictability of the interpersonal trust scale and the connectivity of vmPFC→dACC (d) and vmPFC→IPS (e). The correlation between the connectivity of dACC→vmPFC and the factors of sincerity (f).

**The generalization of the two processes in the cross-cultural sample
and their different roles during a public emergent event**

To investigate whether the two processes of dishonesty coexist in countries with various cultures and whether their effects on the propagation of self-interest-driven dishonest behaviors could be replicated in samples with diverse cultural backgrounds, in Study 4, we recruited participants from 22 countries ($N=1759$) to participate in Phase Two of the coin-flip task used in **Study 1b** and **Study 2**. In addition, we measured participants' attitudes toward epidemic control to examine how these two processes of dishonesty impacted people's coordinating behaviors during the COVID-19 pandemic, when coordination was necessary for public health but came at the cost of self-interest for each individual (**Materials and Methods**). We predicted that rational self-interest propensity would be associated with an individual's inclination toward deviant behavior when one's life is at risk and that dishonesty conformity, on the other hand, would be related to the tendency to comply with authority and conform to others' behaviors.

The results of the current cross-cultural sample revealed that these two processes of dishonesty coexisted when cheating could not be detected individually (rational self-interest propensity θ : $MD=0.12$, $SD=0.66$, $t(1758)=7.66$, $p<.001$, Cohen's $d=.18$, 95% CI: [0.09, 0.15]; conformity learning rate α : $MD=0.39$, $SD=0.36$, $t(1758)=45.1$, $p<.001$, Cohen's $d=.975$, 95% CI: [0.37, 0.41]). In addition, the **Comprehensive Model**, which includes these two processes, was better at explaining participants' behaviors than the other two reference models (RMs), which exclude one of the two

processes in all countries (**Figure S15**). However, the two processes differ across countries (rational self-interest propensity θ : $F(21, 1737)=3.91, p<.001, \eta_p^2=.045$, **Table S7, Figure 8a**; conformity learning rate α : $F(21, 1737)=1.98, p=.005, \eta_p^2=.023$, **Table S8, Figure 8b**). We found an enhancing effect of rational self-interest propensity ($B=0.53, SE=0.022, t(1730)=24.4, p<.0001$, **Figure S16**) and dishonesty conformity on profitable reports across countries ($B=0.18, SE=0.020, t(1730)=9.04, p<.0001$). Moreover, the effect of dishonesty conformity was moderated by the rational self-interest of individuals ($B=-0.32, SE=0.030, t(1729)=-10.7, p<.0001$, **Table S5**). Similar to the result of Study 1b, the promoting effect of dishonesty conformity was more salient in individuals with low levels of rational self-interest ($B=0.37, SE=0.03, t(1729)=12.5, p<.0001$), while the effect decreased to a nonsignificant level in those with high levels of rational self-interest ($B=-0.038, SE=0.03, t(1729)=-1.25, p=.21$). A correlation between SVO and rational self-interest propensity was also found ($B=-0.098, SE=0.032, t(1749)=-3.1, p=.002$, **Table S11, Figure S17**), replicating the findings of **Study 1b**.

The effects of the two dishonest processes on individuals' responses to epidemic control and the efficiency of local pandemic containment. In the cross-cultural experiment, we measured participants' responses to epidemic control, including the tendency to break regulations based on determining how likely they would be to break quarantine rules if they were infected and their life was at risk, knowing that doing so would lead to a high probability of spreading the disease (see **Supplementary**

Materials for a description of the survey). We also measured how much the participants would be willing to stay at home during the pandemic if it were demanded by the local government (the tendency of compliance) or favored under a voluntary code of conduct of people nearby (the tendency of conformity). We found that even after controlling for the effect of individuals' concern about the pandemic and their beliefs in the efficiency of the local government, rational self-interest propensity still predicted individuals' rule-breaking tendencies ($B=0.20$, $SE=0.069$, $t(1744)=2.85$, $p=.0045$), whereas dishonesty conformity was not related to the tendency of violation ($B=0.053$, $SE=0.13$, $t(1744)=0.42$, $p=.67$, [Table S12](#)). Moreover, we found that the proportion of prosocial individuals in the country (measured by the SVO scale) interacted with the rational self-interest propensity to predict an individual's rule-breaking tendency ($B=0.028$, $SE=0.006$, $t(1743)=4.38$, $p<.0001$), suggesting that a positive association mainly exists in countries where the prosocial orientation is more popular ($B=0.53$, $SE=0.10$, $t(1743)=5.14$, $p<.0001$, [Figure S18](#), [Table S13](#)) and not in countries where this orientation is less prevalent ($B=-0.070$, $SE=0.097$, $t(1743)=-0.73$, $p=.47$).

In the country-level analysis, we further compared the similarity patterns of the average rational self-interest propensity and average rule-breaking tendency between countries (**Materials and Methods**). We found that the similarity pattern of rational self-interest propensity between countries also resembled the similarity pattern of the rule-breaking tendency (Spearman's $r=.22$, $p=.00096$, [Figure 8c](#)). On the other hand, the similarity pattern of dishonesty conformity between countries was related to the

similarity in compliance to government regulations (Spearman's $r=.26$, $p=.000049$, [Figure 8d](#)) as well as to conformity to others' coordinative behaviors (Spearman's $r=.22$, $p=.0006$, [Figure 8e](#)).

To investigate how these two processes of the dishonesty of countries impact the efficiency of local epidemic control, we used data of confirmed cases per day from the first wave of the COVID-19 pandemic (see **Materials and Methods** and **Supplementary Materials** for the duration of data collection) to fit a sigmoid model ($y = \frac{a}{1 + e^{-K(x-x_c)}}$; Koivu-Jolma & Annala 2018) and estimated the slope parameter K (which reflects the speed of epidemic control) and the parameter of inflection point x_c (which reflects the delay to the inflection point of the epidemic curve). We found that neither average dishonesty conformity nor rational self-interest propensity of countries was directly related to the overall speed of epidemic control (K) or the delay of the inflection point (x_c) ($ps>0.39$, [Tables S14-15](#)). However, we found that the average dishonesty conformity of the country interacted with the average level of trust (i.e., trust in nearby others to voluntarily coordinate the regulation of epidemic control; see **Materials and Methods** for details) to predict the efficiency of epidemic control of the countries (K : $t(12)=5.02$, $p=.00030$; x_c : $t(12)=-4.30$, $p=.001$, [Tables S16-17](#)). We found that in countries with a higher average belief of trust, a higher level of dishonesty conformity was associated with faster control and a shorter delay of the inflection point (K : $B=0.31$, $SE=0.078$, $t(12)=4.02$, $p=.0017$; x_c : $B=-.276$, $SE=.075$, $t(12) = -3.68$, $p=.0032$), while for those countries with a lower average belief of trust, a higher level of dishonesty conformity would, in turn, hamper the country's

836 efficiency of epidemic control ($K: B=-0.19, SE=0.064, t(12)=2.89, p=.014; x_c: B=135,$
837 $SE=61.79, t(12) = 2.19, p=.049, \text{Figure 8f}$). Regarding the effect of rational self-
838 interest propensity, we found that it was moderated by the average rule-breaking
839 tendencies of the countries ($K: t(12)=-2.67, p=.020; x_c: t(12)=2.23, p=.046, \text{Tables}$
840 **S18-19**): for countries in which the rule-breaking tendency was more common, a
841 greater average rational self-interest propensity was related to an extended delay of
842 the inflection point ($B=172.8, SE=68.1, t(12)=2.54, p=.026$), while for those with a
843 weaker average rule-breaking tendency, a higher average rational self-interest
844 propensity was associated with faster local epidemic control ($B=0.48, SE=0.21,$
845 $t(12)=2.34, p=.037, \text{Figure 8g}$).

Figure 8: The distribution of (a) rational self-interest propensity and (b) dishonesty conformity in the cross-cultural sample. c. The correlation between the similarity of the average (median) rational self-interest propensity and the similarity of the average (mean) tendency of rule breaking between countries. d. The correlation between the similarity of average (median) dishonesty conformity and the similarity of the average (mean) tendency of compliance to epidemic control between countries. e. The correlation between the similarity of average (median) dishonesty conformity and the similarity of the average (mean) tendency to conform to others' behaviors between countries. f. The effect of the interaction between average (median) dishonesty conformity and average (mean) belief of trust of countries on the speed of epidemic control (left) and the delay of the inflection point (right). g. The effect of the interaction between the average (median) rational self-interest propensity and the average (mean) rule-breaking tendency of countries on the speed of epidemic control (left) and the delay of the inflection point (right). The size of points represents the sample size of each country, with larger points indicating larger sample sizes. * $p < .05$, ** $p < .01$, *** $p < .001$.

Mini meta-analysis

We conducted a mini meta-analysis to synthesize the effects of the two processes of dishonesty (i.e., rational self-interest propensity θ and dishonesty conformity learning rate α) on the propagation of dishonest reports of Study 1b, Study 2 and Study 4 in which the same coin flip task was employed (**Materials and Methods**). The pooled association between rational self-interest propensity θ and the average reported frequency of tails across three studies was positive and significant ($M r=0.80$, 95% CI: [0.74, 0.85], $Z=13.34$, $p<.0001$, **Figure S22**), revealing a robust effect whereby more than 60% of the variance in the frequency of profitable reports could be explained by the rational self-interest propensity parameter across the studies. On the other hand, we found that the correlation between dishonesty conformity learning rate α and the average reported frequency was subtle ($M r=-0.048$, 95% CI: [-0.16, 0.02], $Z=-0.86$, $p=.39$, **Figure S23**). We further examined the association between the dishonesty conformity learning rate and dishonest reports given various levels of rational self-interest propensity. The results revealed that when rational self-interest propensity was low, the pooled association of the dishonesty conformity learning rate to average dishonest reports was positive and significant ($M \beta=0.30$, $SE=0.017$, $Z=17.4$, $p<.0001$, 95% CI:[0.27, 0.33], **Figure S24**), while no substantial correlation between the dishonesty conformity learning rate and dishonest reports was found when rational self-interest propensity was high ($M \beta=-0.026$, $SE=0.066$, $Z=-0.40$, $p=.69$, 95% CI:[-0.16, 0.10], **Figure S25**). Altogether, these results suggest a primary role of rational self-interest propensity in the propagation of

dishonest reports when individuals learn of others' dishonesty, while the effect of dishonesty conformity mainly exists when individuals' rational self-interest propensity is low.

Discussion

Learning from others' dishonesty is a complicated process that involves various motivations. In the current research, we proposed a comprehensive model to dissociate the processes driven by rational self-interest and dishonesty conformity and distinguished their roles during the social learning of dishonesty. With simulation modeling and empirical studies of samples with diverse demographic and cultural backgrounds, we found that rational self-interest propensity was the primary factor for self-interest-driven dishonest decisions when people knew of others' dishonesty. In contrast, the effect of dishonesty conformity depended on the rational self-interest propensity of the group norm one encountered and that of their own. We found that when people encountered a group norm with mild or intense dishonesty, individuals with weak rational self-interest propensities were more susceptible to the promotive effect of dishonesty conformity on self-interest-driven dishonest behaviors, whereas for those with stronger rational self-interest propensities, an enhanced tendency toward dishonesty conformity did not necessarily lead to an increase in dishonest acts.

However, such an interaction effect was moderated by the certainty of the external rule. We found that when the reward rule was clearly delivered, individuals could make their own decisions to pursue self-interests without learning from the

group norm; therefore, in Study 1b, Study 2 and Study 4, we did not find a promotive effect of dishonesty conformity on dishonest reports in those with stronger rational self-interest propensities. However, when the external rule of reward was unambiguous, we found that participants driven by higher rational self-interest propensities utilized dishonesty conformity as a strategy to avoid loss. This assumption was further supported by the subsequent analysis of the fMRI experiment whereby for those with higher rational self-interest propensities, greater dishonesty conformity was associated with less frequent conformity when the rule was better revealed and learned (see **Supplementary Materials** for more details).

Therefore, our current results seem to contradict the intuition imposed by the previous findings which suggest social learning is detrimental to honesty and would lead to transmissions of dishonest behaviors. By decomposing the processes, we found that rational self-interest propensity was a determinant of dishonest decisions of self-interests, while the effect of social learning on the propagation of self-interest-driven dishonest behaviors was conditional. Such conditional effects are also implied by inconsistent observations of the effect of dishonesty contagion (Bicchieri & Xiao, 2009; Brunner & Ostermaier, 2019; Diekmann et al., 2015; Maux et al., 2021; Rauhut, 2013). Previous studies suggest that people who overestimate or underestimate others' dishonesty made an adaptive response by increasing or decreasing their own dishonest reports, respectively, thereby leading to the mixed effect of social learning on dishonesty. However, in the supplementary analysis of Study 1b, we found that participants adjusted their reports accordingly only when their dishonesty conformity

was high, which reflects a general tendency of conformity to the group norm, while for those with a stronger rational self-interest propensity, they adjusted their reports marginally more when they underestimated others' dishonesty compared to when they overestimated, suggesting an instrumental rationality to utilize external information for self-interests (**Supplementary Materials** and **Figure S4**, Meglino & Audrey, 2004). Altogether, these findings further confirm the discrepant motivations that underline these two types of dishonest behaviors during the contagion of dishonesty.

The neural correlates of dishonesty contagion

We found that increased activation of the cognitive control network mediated the decisions of full lying reports when individuals applied the strategy of dishonesty conformity to serve rational self-interest propensity. This might result from an enhanced process of conflict resolution through self-serving justification when people learned of the dishonest group norm and made exaggerated reports during the contagion of dishonesty. We also found that individuals who made more full-lying reports engaged in higher activations in the anterior area of the superior temporal sulcus when they faced a dishonest group norm. Such a region has also been suggested to respond to social information framed by wording (Wang et al., 2019), implying a process of norm interpretation during the contagion of dishonesty. More concretely, we found that the activation of aSTS was associated with participants' belief of lying in previous peers; however, this was only found in those with low rational self-interest propensity, suggesting that people with various levels of rational

self-interest propensity interpret the dishonest group norm differently during such a process. In individuals with lower rational self-interest propensities, a restrictive honesty norm was held; therefore, a higher activation of the aSTS might reflect a stronger perception of norm violation toward the dishonest group norm, whereas for those with stronger rational self-interest propensities, the honesty norm might be interpreted flexibly, which could be perceived as a descriptive norm and signal the appropriateness of lying (Bicchieri et al., 2018; Diekmann et al., 2015; Gino et al., 2009; Rauhut, 2013; Zou, 2018). We indeed found that the activation of aSTS was associated with more full-lying decisions in individuals with stronger rational self-interest propensities, providing a potential neural mechanism for the previous theories of motivated belief (Bicchieri et al., 2018; Steinel, 2015; Zou, 2018). In addition, in another supplementary analysis, we found that signals in the striatal network strengthened as the group norm became more predictable, and such signals mediated decisions of conformity when individuals' rational self-interest propensity was low (Supplementary Materials and Figure S14). This suggests that when dishonesty conformity is not conducted to maximize self-interest, it reflects a process of group affiliation, a similar process of ingroup conformity (Wei et al., 2019; Wu et al., 2016; Stallen et al., 2013; for a review, Joiner et al., 2017).

In addition to brain activation, we identified the dynamic neural circuit that underlies these two processes of dishonesty. Through Bayesian family model comparison, we found that the dorsal region of the dACC outperformed the vmPFC in serving as a hub to integrate the various processes involved during the contagion of

dishonesty (e.g., the process of conflict control, norm interpretation and valuation, Shen et al., 2021). Compared to the function of vmPFC, dACC is claimed to monitor conflicts and integrate costs and benefits with a form of metaplasticity and trace long-term values, while the effect of vmPFC is more likely to reflect the values of choices of the current trial (Klein-Flügge et al., 2022). In another relevant condition, dACC has also been consistently reported to be involved in dissonance reduction when people justify their choices to restore cognitive consonance (Izuma et al., 2010; Kitayama et al., 2013; Van Veen et al., 2009), thereby shaping the role of dACC in self-serving justification during the contagion of dishonesty. Through PEB analysis, we found that these two processes of dishonesty were encoded by different dynamic interactions between brain regions. For example, we found a negative correlation between the connectivity of aSTS→dACC and rational self-interest propensity, which could result from a decreased concern for norm violation of the dishonest group norm in individuals with a high rational self-interest propensity. Dishonesty conformity, on the other hand, was associated with the connectivity of vmPFC→dACC and vmPFC→IPS, which were also related to the belief of predictability, pointing to the neural circuits that might underlie the causal effect of the belief of predictability on dishonesty conformity. Moreover, we found that the connectivity of dACC→vmPFC encoded the interaction effect between the two processes, with dACC→vmPFC positively correlating to rational self-interest propensity only when dishonesty conformity was high. We also found that the strength of this connectivity was related to individual differences in the measurement of honesty personality. Such findings

indicate a potentially enhanced process of top-down conflict control over valuation when the strategy of dishonesty conformity was adopted to serve the rational self-interest propensity. A refined experimental design (e.g., conditional modulations) could be employed to target these dynamic interactions to further verify related neurocognitive processes in future studies.

The distinctive effects of the two processes on the containment of COVID-19

The global pandemic of COVID-19 has presented major tests for human society, and the situation was significantly worse in the initial phase, when knowledge of the disease was limited and efficient means to contain the spread of the disease were lacking (Haug et al., 2020). During such a period, nonpharmaceutical interventions (e.g., quarantine, mask-wearing and social distancing policies) are key measures to control infection; however, they require strong community coordination (Haug et al., 2020; Perra, 2021). Dishonest behaviors such as concealing potential exposure to the virus or breaking regulations of social distancing caused great damage to the effect of NPIs in practice (Teo et al., 2020). Therefore, learning how our communities react to the outbreak of such a public emergent event when everyone's interest is concerned is crucial for the development of tailored plans for the local government to contain similar infectious diseases. In our cross-cultural experiment, we found that when lives were threatened, people with strong rational self-interest propensities were more likely to break the regulation of epidemic control for self-interests; however, such a relationship existed only in countries where most people tended to place their self-

interests before others' benefit. This finding is consistent with the assumption of rational self-interest theory that when the environment is self-oriented, people might be less likely to obey regulations by risking their own lives, which might lead to a failure of epidemic control. Therefore, breaking regulations to seek better medical resources has become a rational choice (Meglino & Korsgaard, 2004; Murphy, 2008; Woon & Kanthak, 2019). Such an assumption is supported by the current result on the interaction between the average rational self-interest propensity and rule-breaking tendency to some extent. We found that in countries where rule-breaking tendencies were more prevalent, a higher average rational self-interest propensity of the country was associated with a longer delay of the inflection point, reflecting a prolonged containment of the disease, while in countries where rule breaking was rare, a higher average rational self-interest propensity was actually associated with a shorter speed of epidemic control and a similar trend of effect in the delay of the inflection point (Figure 8g). This effect could result from the emerging advantages of societies with high average rational self-interest in their efficiency of resource allocations through a liberated market encouraged by the high rational self-interest propensity of society, therefore promoting the efficiency of local epidemic control when most people refrain from misbehaviors (Huang et al., 2022). Future study is needed to verify the process that mediates such a relationship.

Regarding the effect of dishonesty conformity, we found that it was related to the tendency to comply with government regulations and conformity to others' behaviors during the pandemic, and moreover, it promoted the efficiency of disease containment

in countries where trust in others' self-constraint was high. These results suggest that a clear and positive norm could facilitate a community of higher average dishonesty conformity to engage in accordant behaviors, and adhering to such norms would help such communities combat an epidemic effectively. While every coin has two sides, a higher level of dishonesty conformity might also lead to a propagation of disorders in a community, especially when most surrounding others are less coordinative, therefore hampering the efficiency of epidemic control (Bavel et al. 2020; Bordia and DiFonzo 2005).

Conclusion

Overall, by constructing a comprehensive model, we provide an inclusive framework to integrate the processes of rational self-interest propensity and dishonesty conformity. We estimate and extract the hidden processes of different motivations that govern individuals' decisions and verify that both exist when people learn from others' dishonesty. Nonetheless, we found that these processes played different roles in the contagion of dishonesty. In addition, we found that these two processes were related to different psychological processes (e.g., self-interest-driven propensity and group affiliation) and neural mechanisms, which are also impacted unevenly by contextual factors such as competition and environmental predictability.

Materials and Methods

Study 1a. Computational modeling. A community of twenty agents was created in the simulation, and among these agents, one was denoted as the “*focal observer*,” and the remaining nineteen were denoted as the “*previous peers*.” To estimate how an agent reported under the influence of others’ behaviors, we built a model of reporting behaviors under the framework of RL (Sutton & Barto, 2011). According to RL theory, the subjective value of the report learned from the group norm ($Q_{env(t)}$) was updated trial by trial according to the discrepancy between the feedback of peer reports and the subjective value in the previous trial ($Q_{env(t-1)}$), termed the PE. The PE was then scaled by the conformity learning rate (α), reflecting the degree to which individuals incorporated the feedback information of the dishonest group norm into the action value when they made their own dishonest reports. Therefore, the RL model of reporting behaviors can be formulated as follows:

$$(1) Q_{env(1)}=2$$

$$(2) Q_{env(t+1)} = Q_{env(t)} + \alpha(FB_t - Q_{env(t)})$$

$$(3) Q_{self(t)} = Q_{env(t)} + \theta$$

Conformity learning rate α is bounded between 0 and 1. $Q_{self(t)}$ indicates the subjective value of the report in trial t , which is the sum of the expectation of others’ reports learned through PEs ($Q_{env(t)}$) and the rational self-interest propensity (θ). We set the initial value of $Q_{env(1)}$ as 2, which is the expected frequency of tails for a fair four-time toss.

1080 Given subjective value $Q_{self(t)}$, the probability of reporting a specific frequency
 1081 P_r ($r \in [0,1,2,3,4]$) is modeled by the sigmoid functions in equation (4) and the
 1082 normalized linking function in equation (5):

$$1083 \quad (4) \quad p_{r_t} = \begin{cases} \frac{1}{1+e^{\frac{-(r_t-Q_{self(t)})}{\beta}-c}}, & r \leq Q_{self(t)} \\ 1 - \frac{1}{1+e^{\frac{-(r_t-Q_{self(t)})}{\beta}+c}}, & r > Q_{self(t)} \end{cases}, \quad r \in [0,1,2,3,4], \quad c=5$$

$$1084 \quad (5) \quad P_{r_i} = \frac{p_{r_i}}{\sum_r p_{r_i}}, \quad r \in [0,1,2,3,4]$$

$$1085 \quad (6) \quad \text{likelihood} = \sum \ln(P_{r_i})$$

1086

1087 As assumed by the model, the parameter of dishonesty propensity (θ) adds an
 1088 overall amount to the subjective value of the report for each trial, which further shifts
 1089 the x-axis position of the peak of the sigmoid functions in equation (4). The
 1090 probability of each report option $r \in [0,1,2,3,4]$ of trial t is generated by the likelihood
 1091 function in equations (4) and (5): when the option was more distant from the peak of
 1092 the distribution, the option was less likely to be adopted and reported (**Figure S1**). β
 1093 in equation (4) indicates the slope of the sigmoid functions, which was of no interest
 1094 in the current study. Therefore, we fixed the values of β and the constant (c) in the
 1095 ABM to minimize the difference between a binomial distribution and the subjective
 1096 value model ($\beta=0.48$, $c=2.5$).

1097 The reports of the agents on a four-coin flip were generated based on the
 1098 probability of each option ($r \in [0,1,2,3,4]$), which was calculated by equations (1) to
 1099 (5). The option with the largest likelihood was defined as the model prediction for

1100 each trial. We first simulated the reports of the coin-flip task in a community of 20
1101 agents, and for each simulation, a group of 16 agents was randomly selected from the
1102 19 previous peers apart from the focal observer to generate the group norm. The
1103 average report of the previous peers was calculated for each trial and provided to the
1104 focal observer to learn. For each of the previous peers, the feedback of others' reports
1105 was generated by the average report of the other community members randomly
1106 sampled from the remaining 18 peers. To investigate how reports evolved in
1107 populations with various levels of conformity learning rate (α) and rational self-
1108 interest-driven propensity (θ), 81 combinations of conditions were constructed with
1109 three levels in each parameter for the "*focal observer*" and the "*previous peers*"
1110 ("*focal observer*": rational self-interest-driven propensity (high $\theta=1.5$ vs. moderate
1111 $\theta=0$ vs. low $\theta=-1.5$) $\times$ conformity learning rates (high $\alpha=0.9$ vs. moderate $\alpha=0.5$ vs.
1112 low $\alpha=0.1$)); "*previous peers*": the rational self-interest-driven propensity (randomly
1113 sampling from distributions centered at 1.5 (intense) vs. 0.5 (mild) vs. 0 (neutral) with
1114 a standard deviation of 2, constrained between -2 and 2) $\times$ the conformity learning
1115 rate (α) (randomly sampled from distributions centered at 0.9 (high) vs. 0.5
1116 (moderate) vs. 0.1 (low) with a standard deviation of 0.1, constrained between 0 and
1117 1)). We simulated seven trials for each agent, and the reports of the focal agent were
1118 recorded. A sample size of 30 "*focal observers*" for each condition was predetermined
1119 to detect a small effect ($f=.1$) of the interactions of interest (Self-alpha $\times$ Self-theta and
1120 Self-alpha $\times$ Other-theta) with a power of .95 at a significance level of .05. We further
1121 validated the findings with various sample sizes ($N=50$, $N=80$, $N=100$), in a

community of 100 agents and in agents with less deviant levels of rational self-interest propensities (high $\theta=1$ vs. moderate $\theta=0$ vs. low $\theta=-1$) and different conformity learning rates (high $\alpha=0.5$ vs. moderate $\alpha=0.3$ vs. low $\alpha=0.1$). Consistent results were found (**Supplementary Materials**).

Study 1b. Participants. A total of 509 participants (225 females, age $M=33.9$, $SD=8.96$) in the United States were recruited through MTurk and completed the experiment on Qualtrics, a professional online survey platform. To eliminate low-effort participants (Crump et al., 2013), participants who did not answer the inspection question of the experimental context correctly and spent an irrational amount of time on the survey (fewer than five minutes or more than two hours) were excluded from the analysis (22.2% of the sample). To ensure the quality of the surveyed data, the Mahalanobis distance (Osborne, 2010) of the remaining samples was calculated based on the responses of the scales of social value orientation (Van Lange & Kuhlman, 1994), honesty-humility of HAXECO personality traits (Lee & Ashton, 2018) and interpersonal trust (Rempel et al., 1985). Responses with a probability of less than 0.001 were identified as outliers and then excluded from the analysis (2.02% of the remaining sample), which resulted in a sample of 388 (176 females, age $M=34.1$, $SD=9.13$). The sample size was predetermined with G*power to validate the existence (significantly different from zero) of both rational self-interest propensity (modeled as parameter θ) and dishonesty conformity (modeled as parameter α). For the first study, to ensure sufficient power, we determined the sample size to detect a small effect

($d=0.2$) with a high power of 95% at an alpha of 0.05 according to a two-tailed one-sample t test ($N=327$). Written consent was provided before each experiment. All studies were approved by the appropriate ethics committee.

Procedure. The participants were first instructed to provide demographic information. Then, they were given a brief introduction to the experiment and were asked questions about the instructions to ensure that they understood the experiment. The participants were instructed to believe that they were playing a seven-trial coin-flip game with an assigned partner, who was randomly chosen from the sixteen participants before them. Then, they were asked to flip a coin five times in private and report the outcome of the first four flips by indicating how many tails they received. They were told that the reward was only dependent on their own performance: they would receive 0.1 dollars for every tail they reported, and the final payment was calculated based on two randomly sampled trials. The experiment involved two phases. In Phase One, the participants were instructed to perform the task without receiving feedback on others' behavior but were asked to guess how the previous participants reported for each trial (**Supplementary material**). For Phase Two, the participants were given feedback on the average reports of the previous sixteen participants for that trial after their self-report to evaluate how they learned from the group norm. We predetermined the feedback sequence by referring to the trend of reports of an independent sample ($N=39$, 25 females) on the same task to ensure ecological validity. We designed the sequence to begin with three fair trials with reports distributed around an expectancy value of 2 (ranging from 1.63 to 2.25),

followed by another four unfair trials with a value of approximately 3 ranging from 2.75 to 3.25. The feedback sequence provided a group norm of mild self-interest-driven dishonesty propensity, which is consistent with the findings of previous studies showing that people refrain from full-lying reports even when punishment or economic loss is absent (Abeler et al., 2019). We held the feedback sequence constant across all participants. At the end of the experiment, the participants were instructed to complete scales of interpersonal trust (26 items, $\alpha=0.94$, Rempel et al., 1985), social value orientation (SVO, 9 items, $\alpha =0.92$, Van Lange & Kuhlman, 1994, **Supplementary materials**) and HAXECO personality honesty-humility (16 items, $\alpha = 0.92$, Lee & Ashton, 2018). The SVO is a nine-item, triple-dominance decomposed measure that distinguishes among prosocial, individualistic and competitive orientations. To include all subjects in the analyses, participants who chose an individualistic or competitive orientation more than six times were classified as proself, while the remaining participants were classified as prosocial (Van Lange & Kuhlman, 1994).

Model estimation. We employed maximum likelihood estimation to fit the RL models to the observed behavior. We estimated the parameters for each participant individually, and the optimal set of parameters that generated the maximum likelihood of equation (6) was obtained using R package MaxLik. To avoid fitting local minima, we applied a grid search over a large domain for the initial value of the parameters (20,000 times) and reported the combination that converged to the lowest negative log likelihood. Bayesian information criteria (BIC) scores summed across participants

were used to compare the models. The likelihood of the random model was calculated based on the binomial distribution of fair coin flips.

Model validation. To validate the efficiency of our proposed comprehensive model (**GM**) in explaining the observed behaviors, we built five other RMs and compared their goodness-of-fit values using BIC, which balance model fit and overparameterization. To examine whether precluding one of the processes would lead to a decrease in goodness-of-model fit for the empirical observations, for the first two RMs, we excluded the parameter of the conformity learning rate (α) and the parameter of rational self-interest propensity (θ), respectively, and obtained a social influence model (RM1) and rational self-interest model (RM2). In RM3, we included separate conformity learning rates for both the positive and negative PEs according to the theory of asymmetric learning proposed in previous research (Gershman, 2015; Cazé & van der Meer, 2013). Considering the plausible inhibition between these two processes driven by discrepant motivations, we proposed another inhibition model that weights the parameters (α and θ) with ratios that sum up to 1 (e.g., $w*\alpha$ and $(1-w)*\theta$) and denoted this as RM4. We also included a random model (RM5) assuming an authentic report strategy; therefore, the reports of participants follow the binomial distribution of a fair four-time toss. The results of model comparisons revealed that the comprehensive model (the GM) outperformed other alternative models in explaining the observed reports of the participants ([Table S1](#)) by achieving a good model fit and model parsimony.

Study 2. Participants. A total of 204 participants from the United States were recruited through mTurk to take part in the online experiment. The data cleaning procedure adopted was identical to that used in Study 1b. Forty-nine participants (24% of the sample) were excluded due to providing incorrect answers to the inspection item about the assigned context, and two others were excluded due to spending an irrational amount of time on the survey (fewer than 5 minutes or more than 2 hours). A sample of 153 participants (77 female, age $M=35.9$, $SD=10.8$) was finalized. The sample size was predetermined to detect a moderate correlation ($r=.2$, according to the result of Study 1b) between the conformity learning rate (α) and the magnitude of variance of the feedback sequence with a power of 80% at $\alpha=0.05$ ($N=153$) and a moderate effect ($f=0.25$) of context (competitive vs. noncompetitive context) on self-interest-driven dishonesty propensity (θ) with a power of 80% at $\alpha=0.05$ ($N=128$). The experiment was conducted using Qualtrics as in Study 1b. No significant difference in gender, age, English fluency, education, employment status, health status, annual family income or SES was found across the groups ($ps>0.129$).

Procedure. The experimental procedure used in Study 2 was identical to that employed in Study 1b. After recording demographic information, the participants were instructed to believe that they were playing a coin-flip game with a randomly assigned partner. They were randomly assigned to one of the six groups based on context (competitive vs. noncompetitive) $\times$ variance of feedback (high vs. moderate vs. low variance). In the competitive context, the participants were told that the

1232 rewards were dependent on both their own performance and that of their partner: the
1233 one who reported a higher frequency of tails won the trial and received a reward of
1234 four yuan, while the other received no reward, and the final payment was calculated
1235 based on the outcome of three randomly sampled trials. In the case of a tie, the reward
1236 would be split. The rules of the game in the noncompetitive context were identical to
1237 those of Study 1b. In the groups with high, moderate and low variance, the
1238 participants were provided with three different feedback sequences: 1.625, 1.25, 2.5,
1239 3.375, 2.75, 3.625 and 3 (high variance, $SD=0.9401$); 2.125, 1.625, 2.25, 3.125, 2.75,
1240 3.25 and 3 (moderate variance, $SD=0.6296$); and 2.375, 2, 2.5, 2.75, 2.625, 2.875 and
1241 3 (low variance, $SD=0.3104$). The mean and fluctuation of the sequences were both
1242 controlled. After the experiment, the participants were instructed to rate how
1243 dishonest in general they thought the previous 16 participants had been on a six-point
1244 Likert scale.

1245 **Manipulation check.** To examine whether the dishonesty of group norms represented
1246 by the feedback sequences was perceived differently between conditions, a 2
1247 (competitive vs. noncompetitive context) $\times$ 3 (low vs. moderate vs. high variance)
1248 ANOVA of the belief of dishonesty in others was conducted. No significant
1249 difference among conditions was found ($F(2,146)=0.667$, $p=0.515$, partial $\eta^2=0.009$),
1250 suggesting that the manipulation of variance and context did not substantially modify
1251 individuals' belief of a group norm of dishonesty.

1252

Study 3. Participants and procedure. We recruited 50 Chinese students from Sun Yat-sen University through advertisements posted on the web to participate in the fMRI experiment as paid volunteers. All participants had normal or corrected-to-normal vision and reported no abnormal neurological history. One participant was excluded from the analysis due to failed behavioral responses, and a sample of 49 participants was finalized (mean age $\pm$ s.d. = 20 $\pm$ 1 years, 26 females). The participants underwent fMRI scanning when playing a dice-rolling task with predetermined feedback from previous peer reports. Three functional sessions of 282 volumes were obtained from each participant, each of which consisted of 15 trials. Prior to the first trial of each session, a reminder screen shown for 6 s was presented to keep the participants focused on the incoming task.

The dice-rolling task. As each session began, a screen presenting option was displayed for 2 s to instruct the participants to select three from the four dice shown on the screen and keep their choices in mind ([Figure 4a](#)). The dice were covered by four gray squares; therefore, the points on the faces were not visible. Following this screen, the outcomes of the dice were revealed and presented for 4 seconds. Then, a response screen was shown, instructing the participants to report the sum of points of the dice they had selected with an interactive slider (ranging from 3 to 18). A red cursor indicating the current choice was initially placed at number 10, which is the midpoint and close to the expectation for the dice-rolling task (10.5). The participants were instructed to respond as soon as possible (within 4 seconds), and the last position of the cursor was recorded as the final decision when the response time was up. We

1275 employed this procedure to simulate a process of random dice rolling, and the
1276 outcome for each dice was generated from a uniform distribution that assumes an
1277 equal probability of 1/6 for each face of the dice to be sampled. After the report phase
1278 with a 0~2 s jitter, a feedback screen was shown for 2 s, and the average report of
1279 points from the 16 previous peers was presented. The participants were told that their
1280 rewards depended both on their self-report and on the report of an assigned partner
1281 who was randomly sampled from the previous subjects for each trial. After the
1282 feedback screen was shown, a fixation was presented with a jitter of 2~6 s, and then a
1283 new trial started. Ten practice trials were provided outside the scanner before the
1284 formal experiment to ensure that the participants were familiar with the rules and the
1285 pace of the task.

1286 Distinct from the previous studies, the participants were told that the rules of the
1287 current task were ambiguous. For some sessions, the participant from the pair who
1288 reported more points would win the game and receive a reward of 4 yuan, while for
1289 the other sessions, the participant who reported fewer points would win. In both
1290 conditions, the participant who lost the game received no rewards, and in the case of a
1291 tie, the rewards were split equally. The participants were also told that the rules of the
1292 session were identical across all the participants; therefore, they could learn from the
1293 reports of the previous participants to determine the current rule. However,
1294 participants were told that the information provided to their previous peers was
1295 different: they would learn the outcome of their reports for each trial (that is, whether
1296 they won the current trial or not) while they did not know the reports of others. The

1297 distribution of the feedback sequence was kept consistent across sessions, which
1298 began with trials fluctuating around the expectancy (10.5) and gradually evolved to a
1299 distribution of overreporting corresponding to the rule (see **Supplementary**
1300 **Materials** for details). For both Block (Session) 1 and Block (Session) 3, the ground
1301 truth of the rule preferred smaller reports, whereas the rule of Block (Session) 2 was
1302 the opposite. This setting created an opportunity for conforming behaviors of various
1303 motivations to emerge. Since the participants did not need to report the dice they
1304 selected in the choice phase, an opportunity to cheat for rewards without being
1305 detected was available. Therefore, for those driven by high rational self-interest
1306 propensities, a strategy of conforming to others' behavior at first when the rule was
1307 unclear and then shift to overreporting when the rule was learned would be adopted to
1308 accumulate evidences of the rule and avoid losses (Toelch & Dolan, 2015). The
1309 instructions were viewed through a projection onto a mirror mounted onto the head
1310 coil of a scanner. After the experiment, participants were asked to rate on a five-point
1311 Likert scale (from extremely dishonest 1 to extremely honest 5) outside the scanner to
1312 indicate how much they thought the previous 16 peers were dishonest. All of the
1313 participants arrived in a prearranged order with overlapping timing of arrival to
1314 convince them of the experimental settings. No communication between the
1315 participants was allowed during the experiment. After completing the study, the
1316 respondents were paid fixed compensation for their participation.

1317 **Computational modeling.** We implemented the **Comprehensive Model**, which
1318 comprises both the processes of rational self-interest and dishonesty conformity, to fit

the observed reporting behaviors based on the standard Rescorla-Wagner model (Sutton and Barto, 1998). In the model, the participants updated their belief about the group norm ($Q_{env(t)}$) according to the PEs elicited by the discrepancy between FB and their subjective belief about the environment trial by trial:

$$(7) Q_{env(t+1)} = Q_{env(t)} + \alpha(FB_t - Q_{env(t)})$$

We estimated the likelihood function of the reporting behavior by multiplying a subjective distribution with an objective distribution that was given by the available options for each trial (eq.8-9). To reduce model complexity, we denoted the likelihood function of the subjective distribution as a Gaussian distribution with standard deviation β , centering on the sum of the subjective value learned from the environment ($Q_{env(t)}$) and the individual self-interest driven propensity (θ).

$$(8) p_{obj}(c) = \frac{\exp(v_c)}{\sum_c^{options} \exp(v_c)}$$

$$(9) p_{comb} = p_{subj}^p * p_{obj}^{2-p}$$

In Eq. 8, v_c is an objective value assigned to the four available choices (c) in the outcome. We first estimated v_c as a free parameter; however, including v_c as a free parameter did not improve the goodness of fit (BIC = 9360.2). Therefore, we fixed the value as 4 by referring to the mean of the estimates (the estimation of v_c for Block 1: 3.58, Block 2: 3.55, and Block 3: 3.80).

The conformity learning rate (α), self-interest propensity (θ), dispersion of the subjective distribution (β), initial value of the belief of the environment (init) and power exponent of the subjective distribution (p) were estimated for each participant and block by maximizing the likelihood of the observed choices. The estimation was

performed using the maxLik package in R. Blocks (8.84%) were excluded from analysis when a participant consistently reported the (wrong) optimal choices in the last six trials of the block, indicating a failure to learn the rules of the game. One participant reported the optimal choices of the opposite side for more than 80% of the last ten trials in one block and were also excluded from the analysis. Consistent results were found on the completed sample (**Supplementary Materials**).

Candidate computational models. To validate the efficiency of the comprehensive model in explaining the observed behaviors, we built nine alternative models based on various assumptions of the learning processes, including the reference models (RM 1 and RM 2), which include only one of the two processes (i.e., the social influence model excluding parameter θ and the rational self-interest model excluding the process of dishonesty conformity), a random model (RM3) in which the likelihood function was solely determined by the objective distribution, and a dynamic model including a dynamic learning rate which decays (RM4a) or increases (RM4b) as the variability of the feedback increases (**Supplementary Materials**). Consistent with the previous experiments, the comprehensive model outperforms other alternative models and achieves both a good model fit (a higher likelihood) and model parsimony (a smaller BIC, **Table S4**).

fMRI data acquisition and preprocessing. Brain images were acquired using a 3T Siemens Magnetom Prisma scanner with a 64-channel head coil at Sun Yat-sen University (Guangzhou, China). Functional images were acquired using T2-weighted echo-planar imaging pulse sequences (TR=1000 ms; TE=30 ms; field of view=220

mm; flip angle=60°; voxel size = 2×2×2mm³), with each volume comprising 64 slices of 2 mm thickness. The multiband acceleration factor was 2. Anatomic images were acquired using a T1-weighted, magnetization-prepared rapid gradient echo sequence (TR=2200 ms; TE=2.26 ms; field of view=256 mm; flip angle=8°; voxel size = 1×1×1 mm³). The phase-encoding direction ran from anterior to posterior (A >> P). The first 6 volumes of each time series were discarded to account for T1 equilibrium effects.

Functional images were processed using SPM12 software (the Wellcome Trust Center for Neuroimaging, London, UK). Head movements were corrected within each session, and six movement parameters (translation: x, y, z; and rotation: pitch, roll, yaw) were extracted for further analysis in the statistical model. The mean realigned functional image was normalized to the standard Montreal Neurological Institute (MNI) template. The functional images were resampled to 3×3×3 mm³ voxels and then spatially smoothed using an isotropic 8 mm full-width half-maximum Gaussian kernel. Excessive motion exceeding 3 voxel sizes was predefined as an exclusion criterion for the whole dataset. Movement parameters were manually inspected for excessive head movement, and no participant had to be excluded due to excessive motion. After preprocessing, a manual check was also performed to determine whether images after normalization were matched with the template.

fMRI data analysis.

GLMs: For both GLMs, the onsets of the four experimental phases (i.e., choice, outcome, report and feedback, [Figure 4a](#)) were included as regressors, and to control the confounding effects of motion and cognitive demands on calculation, in GLM 1,

1385 we included the frequency of button pressing and reaction time as modulators of no
1386 interest. For GLM 2, a parameter modulator of the feedback phase that denotes the
1387 disadvantages of participants' self-reports compared to feedback was included to
1388 control the effect of loss. Six head motion regressors were included as nuisance
1389 regressors for both GLMs. All regressors were convolved with the canonical
1390 hemodynamic response function. A 128-sec temporal high-pass filter and first-order
1391 autoregressive model were applied to remove low-frequency noise and serial
1392 correlations, respectively. For the group-level analysis, the percentage of reports
1393 driven by the rational self-interest of each participant in each round was entered as the
1394 covariate and regressed on the beta estimates derived from the first level to investigate
1395 the neural correlates of rational self-interest-driven dishonest behaviors during the
1396 report (GLM 1) and FB phases (GLM 2). The whole brain analyses were thresholded
1397 and displayed at $P < 0.05$ clusterwise familywise (FEW) error rate corrected with a
1398 cluster-forming threshold of $P_{\text{unc.}} < 0.005$. For GLM 1, we extracted the beta values of
1399 each participant for each block and obtained the average beta value with sphere masks
1400 (5 mm) centered at the significant clusters' peak. For GLM 2, the beta estimates of
1401 vmPFC and aSTS were extracted using a sphere mask centered at coordinates [0, 16,
1402 18] and [-57, -27, -12] (Saxe & Kanwisher, 2003), respectively.

1403 **Dynamic casual modeling.** Bilinear, nonstochastic DCMs were estimated separately
1404 for each subject and experimental session. ROIs were defined with the brain regions
1405 identified by GLM 1 during the report phase (dACC, x, y, z = 0, 16, 38; right IPS, x,
1406 y, z = 38, -58, 44; right IFG, x, y, z = 46, 20, 20) and those identified by GLM 2

1407 during the FB phase (left aSTS, x, y, z=-58, -28, -12; vmPFC, x, y, z=-2, 36, -10).
1408 Spheres of 5 mm centered at the coordinate were defined, and volumes of interest
1409 were extracted as the eigenvariate of the participant's BOLD time course within the
1410 region. Bayesian random effect that assumes subject heterogeneity in the best model
1411 that accounts for the data was employed for model comparison. Exceedance
1412 probabilities were used for the evaluation of model fit, which expresses the
1413 probability that a model or models of a family (that share common features) are more
1414 frequent than other models in the population (Stephan et al., 2009).

1415 **Model specification and Bayesian model selection for DCM.** We specified an
1416 architecture in which the presentation of the report screen (action cue) elicited activity
1417 in regions of the frontoparietal network identified in GLM 1, whereas the presentation
1418 of the FB screen (group norm) elicited activations in aSTS and vmPFC, which were
1419 identified by GLM 2 (Stephan et al., 2010; Harding et al., 2015). We assume a model
1420 structure with a hub region (dACC vs. vmPFC) that connects other regions and
1421 integrates values of the different processes, including learning of the dishonest group
1422 norm and the tendency to pursue self-interest when cheating was undetectable ([Figure](#)
1423 [6](#)). We then compared models from these two families to verify the model structure
1424 that was more plausible given the measured fMRI signals. To restrict model space,
1425 reciprocal interactions between regions within the frontoparietal network were
1426 assumed based on anatomical findings (Parlatini et al., 2017) and previous DCM
1427 protocols (Harding et al., 2015; Wang et al., 2010). Since this is the first study to
1428 investigate the dynamic interactions of networks that underline rational self-interest-

1429 driven dishonest behaviors during the contagion of dishonesty, we employed a
1430 factorized design with a grid search to construct the model space by including the
1431 following factors: (1) the region of hub (dACC vs. vmPFC); (2) the structure of
1432 connection within the prefrontal cortex, and specifically, the number of nodes of the
1433 frontoparietal cortex connected to vmPFC; (3) (reciprocal or) directional interaction
1434 between the connected nodes; and (4) nodes that receive driving inputs (i.e., the inputs
1435 of action cues for the report phase and information of group norms for the feedback
1436 phase, respectively). We identified the family of models that best explained the data at
1437 the population level through a three-stage model comparison (Roy et al., 2014;
1438 Lindström et al., 2018). For the first stage, we determined the structure of the DCM
1439 by comparing families constructed by factors and factor two (**Figure 6a**). For the
1440 second stage, we identified whether these regions were reciprocally or directionally
1441 connected by comparing models of all possible connection patterns nested within
1442 families. For the last stage, we identified the regions that received stimulus input by
1443 comparing models in a factorized manner (**Table 3**). Irrelevant factors were fixed as
1444 reciprocal interactions (for Stage One) or full impacts of the driving inputs on nodes
1445 (for both Stages One and Two). The structure that outperformed the alternatives
1446 entered the next step. With the design, a total of 116 models were identified (14
1447 models for Stage 1, 81 models for Stage Two, and 21 models for Stage 3). Via family
1448 rfx-BMS analysis, the model structure with dACC serving as a hub region was
1449 determined ($X_p = 1$, **Figure 6b**), with all nodes of the frontoparietal network

1450 interacting with vmPFC ($X_p = 1$, **Figure 6c**), reciprocal interactions ($X_p = 1$, **Figure**
1451 **6d**) and a full impact of driving inputs ($X_p = 0.51$, **Table 3**).

1452 **PEB analysis.** We employed PEB analysis to examine which of the effective
1453 connectivities within the network encode rational self-interest propensity and
1454 dishonesty conformity. For each PEB model, we built a 2nd level design matrix by
1455 including the group mean of connectivity strength and the parameter of interest
1456 (rational proself interest or dishonesty conformity) as the covariate. Age and gender
1457 were included as nuisance variables. Bayesian model reduction (BMR) with an
1458 automatic search was performed to compare the estimated PEB (full) model against
1459 reduced models that had certain parameters “switch off” by fixing the prior
1460 expectations as zeros (Friston et al., 2016). Parameters that did not contribute to the
1461 model evidence were eliminated to reduce model redundancy. To ensure robustness,
1462 we thresholded the results with very strong evidence (a posterior probability of 0.99)
1463 with the parameters present rather than absent. The Bayesian model average (BMA)
1464 was applied to summarize parameters across models by averaging the parameters of
1465 different models weighted by their posterior probabilities (Hoeting et al., 1999; Penny
1466 et al., 2006).

1467 **Leave-one-out cross validation.** We further examined whether the individual
1468 parameters of proself interest (θ) or dishonesty conformity (α) could be predicted by
1469 the intrinsic connection identified by the PEB analysis through leave-one-out cross
1470 validation (Zeidman et al. 2019). By iterating the step for all of the subjects, the
1471 prediction value of the parameter was obtained and further compared to the

observation across subjects using Pearson correlation analysis. A correlation of above the chance level signifies a substantial association between the effective connectivity and the parameter of process.

Study 4. Participants. To verify the process of rational self-interest propensity and dishonesty conformity in each country, we determined the sample size of Study 3 using G*Power based on the effect size obtained in Study 1b ($d=0.4$) with 80% power at an $\alpha=0.05$ ($N=52$) for each country before data collection. We recruited at least 55 local residents from each country and collected samples from as many countries as possible from the MTurk platform and collaborators in different countries. The recruitment of participants started in early April 2020 and ended in early June 2020. A total of 2265 participants from 23 countries completed the experiment. The same data cleaning process as that use in Study 1b and Study 2 was employed, whereby participants who incorrectly responded to the inspection item of instructions (12.5% of the sample) or spent fewer than 5 minutes or more than 2 hours (7.2% of the sample) on the survey were excluded from the analysis. Questionnaire responses (including the scale of social value orientation and items about attitudes toward COVID-19) with a probability less than 0.001 in the distribution of Mahalanobis distance were identified as outliers and excluded from analysis (2.1% of the remaining sample). Data from Argentina were further dropped from the analysis due to an inadequate sample size (6 participants). As a result, a sample of 1759 participants from 22 countries was finalized ([Figure S21](#)).

1494 **Procedure.** Participants from different countries participated in Round Two of
1495 the experiment of Study 1b. After finishing the coin-flip game, the participants were
1496 instructed to complete the SVO scale ($\alpha=0.83\sim0.98$) and self-construal scale
1497 ($\alpha=0.71\sim0.91$) and to answer several questions concerning the COVID-19 pandemic,
1498 including questions on their attitudes on pandemic control in their countries, their
1499 tendency to break quarantine regulations upon being infected and the extent to which
1500 they trusted their neighbors to declare their trips truthfully even at the cost of
1501 quarantine rules (see **Supplementary Materials** for a detailed description of the
1502 items). The experiment was conducted using Qualtrics, and all instructions and items
1503 were translated into local languages by professional translators with back translation.

1504 **The indicators of epidemic control of K and x_c .** We used the data of confirmed
1505 cases per day during the COVID-19 pandemic from the *Johns Hopkins University*
1506 *Center for Systems Science and Engineering (JHU CSSE, Dong et al., 2020)* to
1507 estimate the parameters of the overall speed of pandemic control (K) and the delay of
1508 the inflection point (x_c) for each country. We used data from the date on which daily
1509 confirmed cases in the country reached 100 cases for the first time to those for the
1510 date preceding the second outbreak in the country (Salvador et al., 2020). All data
1511 collection was completed before August 4th, 2020 (**Table S6**). A sigmoid function
1512 ($y = \frac{a}{1 + e^{-K(x-x_c)}}$) was employed to estimate slope parameter K (which reflects the
1513 speed of epidemic control) and the parameter of infection point x_c (which reflects the
1514 delay of the inflection point of the epidemic curve; Koivu-Jolma & Annala, 2018). A
1515 larger K (or a smaller x_c) indicated less time taken by the country to reach a plateau of

total confirmed cases, which reflects greater effectiveness of local containment of the pandemic ([Figure S19](#)).

Representational similarity analysis. By calculating the pairwise absolute difference of values between countries, a 22×22 -dimensional matrix of distances was built for each variable to describe the overall representational pattern of dissimilarity of the tested variables between countries. These difference scores were transformed into $[0,1]$ intervals ($S_{ij_{trans}} = 1 - D_{ij_{raw}} / \text{Max}(D_{ij_{raw}})$) as similarity scores. Since the matrices are symmetric along the diagonal, the lower triangle was obtained for each matrix, resulting in a vector containing $(22 \times 22 - 22) / 2 = 231$ values for each tested variable. Spearman's correlation was applied to test the correlation between the similarity matrices, and a positive correlation indicated a similar country-level representational space between the two tested variables from which the similarity matrices were derived.

Mini meta-analysis. We included all participants of Study 1b, Study 2 and Study 4 in our first-hand data since the same coin-flip task was employed in these studies. To estimate the combined effect of rational self-interest propensity θ and dishonesty learning rate α on the dishonest reports that participants made, we first converted the correlation coefficients between the two parameters and the average reported frequency of tails with Fisher's r to z transformations. Then, we pooled the effect sizes of the three studies by assuming a random-effect model on the true effects following steps given in Harrer et al. (2021). Regarding the meta-analysis of the relationship between the dishonesty conformity learning rate and dishonest reports

under different levels of rational self-interest propensity, we calculated the standardized regression coefficients (i.e., the beta value) of dishonesty conformity when the rational self-interest propensity of individuals was low (1 SD below the mean) and high (1 SD above the mean) and then pooled the effect sizes of regression coefficients over studies with a random-effect model. We conducted mini meta-analyses with the meta package of R and created forest plots to present the combined effects ([Figure S22-S24](#)).

Data availability

Consent was not obtained to publicly share individual participant data. However, grand average behavioral data used for analysis and modeling are available at https://osf.io/xq8b7/?view_only=9bb5408456bc4e0f85133e79eeb95c0c, and other data are available from the corresponding author on request.

Code availability

All codes are available at https://osf.io/xq8b7/?view_only=9bb5408456bc4e0f85133e79eeb95c0c

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Author contributions

HLQ and LSY designed the study; HLQ, HGL, LQY, ZYM and LSY conducted the experiments; HLQ and LSY analyzed the data; and HLQ and LSY wrote the manuscript. All authors commented on the manuscript.

1561 Compliance with ethical standards

1562 **Conflict of interest statement** On behalf of all authors, the corresponding author
1563 states that there is no conflict of interest to report.

1564
1565 **Ethical approval** All procedures performed in studies involving human
1566 participants were done in accordance with the ethical standards of the respective
1567 institutional and/or national research committee and following the 1964 Helsinki
1568 declaration and its later amendments or comparable ethical standards.

1569
1570 **Informed consent** Informed consent was obtained from all individual participants
1571 included in the study.

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