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May the odds — or your personality — be in your favor: Probability of observing a favorable outcome, Honesty-Humility, and dishonest behavior

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Abstract

In the light of the potential negative consequences of dishonest behaviors for individuals and societies, researchers from different disciplines have aimed to investigate situation and person factors shaping the occurrence and extent of such behaviors. The present study investigates the roles of a situation factor, the baseline probability of observing a favorable outcome, and a person factor, trait Honesty-Humility from the HEXACO Model of Personality, in shaping dishonest behavior. Next to main effects, a person-situation interaction between these factors was tested. Across three studies with 5,297 participants overall, we find that a higher baseline probability of observing a favorable outcome and lower levels in Honesty-Humility are linked to more dishonest behavior, whereas there was no strong evidence for an interaction between these factors. By testing the assumed effects in two different cheating paradigms, this study additionally allows to disentangle previously found effects of (a) the distance between an observed and the favorable outcome and (b) the baseline probability of observing a favorable outcome.

Keywords: dishonesty, cheating, Honesty-Humility, person-situation interaction, baseline probability

1 Introduction

Dishonest behavior can entail negative consequences for individuals and societies. Examples of such negative consequences span from people suffering due to false rumors (Hinduja & Patchin, 2010), to countries suffering from corruption (Transparency International, 2019), to fraudulent behavior contributing to a global financial crisis (Fligstein & Roehrkasse, 2016; Thakor, 2015).

In the light of these and other consequences, researchers from different disciplines have aimed at identifying factors affecting the occurrence and/or extent of dishonest behavior. Many of such factors represent situational characteristics (situation factors) that have been suggested to make it more or less likely that dishonest behavior occurs. Examples include cues signaling observability of the actor (e.g., Gneezy, Kajackaite & Sobel, 2018; Schild, Heck, Ścigała & Zettler, 2019), the size of an incentive following dishonest behavior (e.g., Gneezy, Kajackaite & Sobel, 2018; Hilbig & Thielmann, 2017), or induced commitment to honesty (e.g., Heinicke, Rosenkranz & Weitzel, 2019; Kleinlogel, Dietz & Antonakis, 2018).

Next to field studies (for a review, see Pierce & Balasubramanian, 2015), in experimental research, dishonest behavior is often examined via behavioral cheating paradigms (Gerlach et al., 2019). Many of such paradigms include conditions in which participants can anonymously claim having obtained a certain outcome (in a task, lottery, or the like) in order to obtain an incentive. In the classic dice-rolling paradigm (e.g., Fischbacher & Föllmi-Heusi, 2013; Gächter & Schulz, 2016), for instance, participants are informed that a certain outcome of a die roll entails a monetary bonus for them. Following that, participants roll a die in private and are asked to report the number they rolled. In a structurally similar and also frequently used task, the coin-flip paradigm (e.g., Hilbig & Zettler, 2015; Pfattheicher, Schindler & Nockur, 2018), participants have to toss a coin and to report whether the outcome matches a desired outcome (e.g., "Heads") to obtain a bonus. These frequently used paradigms — in their recent meta-analyses, Gerlach et al. (2019) found 129 experiments using the dice-rolling paradigm and 163 experiments using the coin-flip paradigm, respectively — seem very similar and even interchangeable in many regards. Importantly, though, these paradigms often differ with regard to a potentially crucial situation factor: the baseline probability p of observing a true favorable outcome (i.e., an outcome that leads to a positive consequence such as a monetary payoff without the need for cheating). That is, in the classic dice-rolling paradigm p of actually observing a specified target

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number (e.g., a "6") is 16.67%, whereas in the one-shot coin-flip paradigm p of actually observing a specified target outcome (i.e., "Heads" or "Tails") is 50%. Thus, winning without cheating (when asked to report the actually observed outcome) is more likely in the one-shot coin-flip paradigm as compared to the classic dice-rolling paradigm.[1] Importantly, p can vary not only among different versions of experimental cheating paradigms but also among real life situations, given that any event in which one can show dishonest behavior and/or obtain a favorable outcome without showing dishonest behavior can be more or less likely. Yet the effect of baseline probability of observing a favorable outcome has been examined only sparsely, so far.

More precisely, both Abeler, Nosenzo and Raymond, (2019) and Heck, Thielmann, Moshagen and Hilbig (2018) recently argued that p could influence dishonest behavior. Indeed, it seems likely that a higher p increases the believability and excusability — and, in turn, the occurrence — of dishonest behavior. For example, one would hardly doubt that someone rolled a die in private and scored a number higher than 2 (p = 2/3), whereas one would be more doubtful if someone reports to have rolled a "Yahtzee"[2] with only one try (p < 0.0001) in private. Thus, an increasing p provides participants with an increasing legitimization to report a desired outcome. Supporting this view, previous studies have shown that people are more likely to cheat when a situation is ambiguous and, in turn, allows for self-serving justifications to behave unethically (Bassarak et al., 2017; Shalvi et al., 2011). Relatedly, if $p = 0$ (i.e., not ambiguous at all), every reported win reflects dishonest behavior (if reporting a win due to a misunderstanding, mistake, or the like can be ruled out), so that participants' privacy when reporting an (desired) outcome is also conflated with p (see, e.g., Hilbig, Moshagen & Zettler, 2015; Ljungqvist, 1993). Consequently, increasing ps should lead to higher cheating rates, other things being equal.

Evidence for such an effect was provided by a recent study by Abeler et al. (2019). Specifically, when raising p from 10% to 60%, overreporting (i.e., cheating) increased by almost 30%. Following up on this, Garbarino, Slonim and Villeval (2017) reanalyzed 81 studies (N = 36,668) differing in p, finding that cheating rates are higher in studies with higher p. Importantly, though, it should be noted that in the reanalyzed studies using a binary winning/losing design, p was always ≤ 60%. This means that none out of 81 studies used a scenario in which winning legitimately was very likely (i.e., > 60%).

Based on this lack of information in previous data, Garbarino et al. (2017) conducted a study investigating cheating rates also in a scenario with high winning probabilities. In this study, participants played a mind coin-tossing game in which they had to toss a coin three times but before each toss they had to predict which side of the coin will end up face-up; p was manipulated by the number of correct guesses needed to obtain a win. In a condition with p = 87.50% (i.e., at least one correct guess needed) cheating rates were significantly higher than in a condition with p = 12.50% (i.e., three correct guesses). In contrast to this, another recent large scale reanalysis of cheating paradigms (N = 5,002; Heck et al., 2018) showed inconsistencies with the findings described above. Specifically, Heck et al. reanalyzed data collected in 16 studies and found no systematic influence of p on cheating rates, such that cheating rates were not higher in studies with higher (or lower) p. Importantly, though, the studies used in this reanalysis had a small range of p, namely, 0.16% to 50%, with most of the studies (10 out of 16) using exactly p = 25%.

Taken together, the evidence for an influence of p on cheating rates is inconsistent, maybe because p has mostly been ≤ 60%. Consequently, we will thoroughly test whether there is a relation between p and dishonest behavior. More precisely, building on the theorizing, findings, and limitations described above, we started our series of investigation with testing the main effect of p on dishonest behavior across eight conditions with a broad range of ps. We hypothesized that the proportion of dishonest individuals would increase with p.

2 Study 1

2.1 Method

2.1.1 Design, materials, and procedure

We set up an online study using the survey framework formr (http://www.formr.org; Arslan, Tata & Walther, 2018), recruiting a sample via the survey panel Amazon Mechanical Turk (http://www.mturk.com/). We invited only US residents with an approval rating of 95 or higher. The study was preregistered on the Open Science Framework (OSF; https://osf.io/b7vzd/). After entering the study, participants received basic information about the study, gave consent to participate, and provided some demographic information. Afterwards, they participated in a variant of the coin-toss task (e.g., Zettler, Hilbig, Moshagen & de Vries, 2015) in

[1]Note that there are different versions of the dice-rolling paradigm, the coin-flip paradigm, and other cheating paradigms. For example, some studies (e.g., Hilbig & Zettler, 2015) ask participants to conduct two coin flips in a row, and an incentive is given only if participants report a certain outcome of two coin flips (resulting in a p of 25%). More generally, all these paradigms can be administered with a similar p (e.g., having rolled a number higher than 3 in one dice-roll with a six-sided dice and observing "Heads" in one coin-flip, respectively, both have a p of 50%). However, the "standard" p often differs across paradigms and studies.

[2]A Yahtzee describes the event of having rolled the same number with each of five dices (e.g., five times a "4") in the well-known dice game "Yahtzee".

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Table 1: Overview of the conditions. “Heads” is the minimum number of “heads” needed to win the incentive.

Condition	p	“Heads”	N	d
1	1.76%	12	67	.29
2	5.92%	11	48	.42
3	15.09%	10	60	.35
4	30.36%	9	69	.50
5	50.00%	8	73	.34
6	69.64%	7	102	.64
7	84.91%	6	192	.48
8	94.08%	5	447	.36

which participants were asked to flip a fair coin 15 times and to report the total number of “Heads” observed. Importantly, we manipulated the minimum number of (reported) “Heads” needed to receive a bonus incentive of $0.75 (next to the flat fee of $0.75) between subjects. Specifically, we realized eight conditions in which the number of (reported) “Heads” required to obtain the incentive ranged from at least 5 (p = 94.08%) to at least 12 times (p = 1.76%).[3] For an exact overview of the conditions, see Table 1. To allow feasibility of the study, no higher *ps* than 94.08% were chosen (otherwise, a very large number of people would have needed to be invited in order to investigate cheating, because so many people would have won truthfully). Importantly, participants were informed about p (“The probability to flip at least X “heads” in 15 throws is X.XX %. That means that out of 10,000 participants, X would win on average.”). After the coin-toss task, participants were asked a control question on how high p (in their condition) was (“How high was the probability to flip at least X “Heads” out of 15 throws?”), and were given three possible answers (one correct). In line with our preregistration, this item was used for exploratory analyses.

2.1.2 Analysis plan

The analysis proceeded by using the multinomial processing tree (MPT) framework (e.g., Erdfelder et al., 2009) as implemented in multitree (Moshagen, 2010). The model accounts for the fact that a certain proportion of the observed “win” responses occurs because participants actually obtained the target outcome (and thus did not cheat) by relating the observed responses to two non-observed states, p as well as the proportion of dishonest individuals (d): $p(\text{"win"})_k = d_k + (1-d_k)\cdot p_k$ where p_k is the baseline probability of winning in the k-th condition (which thus becomes a constant), d_k denotes the (estimated) proportion of dishonest individuals, and $p(\text{win})_k$ is the (observed) proportion of participants indicating to have won (for details, see Moshagen & Hilbig, 2017). Note that the model is applied by aggregating the responses of the participants in each condition. This basic structure was applied to all conditions (with different constant p_k parameters representing the actual probability of observing a favorable outcome in the respective condition as well as different freely estimated d_k parameters representing the proportion of dishonest individuals in the respective condition), leading to a joint multinomial model. To test whether there is a difference in the probability of cheating across conditions, equality constraints on the d parameters are placed and the model test statistic (G-squared) was evaluated for significance.

2.1.3 Participants

In order to determine an appropriate sample size for our study, an a-priori power analysis was conducted using multitree (Moshagen, 2010). We assumed the proportion of dishonest individuals (see Moshagen & Hilbig, 2017) to range from 11.65% to 57.96% in the 8 experimental conditions, based on pilot data and assuming dishonesty to decrease linearly with the probability of observing a favorable outcome. Details of the pilot study can be found in the supplemental material (https://osf.io/b7vzd/). The chosen values correspond to an effect size of Cohen’s ω = 0.15 which is considered as a small to medium sized effect (Cohen, 1988). Participants were randomly assigned to the conditions using predefined allocation ratios, $1/(1-p_i)$, to ensure that a larger sample is available in conditions in which the probability of observing a favorable outcome is high (so that only a small fraction of the participants is actually in the position that cheating is necessary to obtain the incentive), thereby realizing an approximately equal standard error for each condition (Moshagen & Hilbig, 2017). Given α = .05, this resulted in a required total sample size of N = 821 for a power of $1-\beta$ = .80 to detect differences across conditions. Considering slight oversampling (10%) and ensuring that every condition has a minimum of 60 participants (with largely balanced gender and age distributions), we planned to collect data from 1,054 participants. Due to slight oversampling on Amazon Mechanical Turk, the final sample size was N = 1,058.[4] Participants were relatively heterogeneous with respect to gender (49.24% female, 50.38% male, 0.37% other) and age (M = 37.17, SD = 11.80 years).

[3]The differences in the percentages are asymmetrical, but reflect possible outcomes (i.e., a coin toss can only result in Heads or Tails).

[4]Please note that this power analysis deviates from the one reported in the preregistration. The power analysis in the preregistration contained a computational error and had to be redone (before the study was completed).

2.2 Results

2.2.1 p and dishonest behavior

Estimated d_i parameters for each condition are displayed in Table 1. Contrary to Hypothesis 1, the proportion of dishonest individuals was not found to be significantly higher in conditions with higher probability ($\Delta G^2(1) = 10.50$, $p = .162$, $\omega = 0.10$). Also when excluding participants that did not answer the control question correctly, the relation was not significant ($\Delta G^2(1) = 11.13$, $p = .132$, $\omega = 0.11$).

2.3 Discussion

Contrary to our hypothesis, we found no support for a relation between p and dishonest behavior in Study 1. Although the proportion of dishonest individuals d was descriptively higher in conditions with higher p, no statistical significant differences were evident. To test whether this was because we overestimated the effect size (i.e., Cohen's $\omega = 0.15$) and therefore recruited an insufficient sample size to reliably capture the effect, we ran a second, highly powered study. In addition, we continued our investigation with additionally considering a well-known personality predictor for dishonest behavior — trait Honesty-Humility from the HEXACO Model of Personality (Heck et al., 2018; Zettler et al., 2019).

2.4 Honesty-Humility and dishonest behavior

Next to situation factors, such as p, researchers have investigated individual difference constructs (person factors) as potential determinants of dishonest behavior. Beyond age and gender, which have been meta-analytically linked to dishonest behavior in cheating paradigms (Gerlach et al., 2019), research has suggested that, for instance, creativity (e.g., Mai, Ellis & Welsh, 2015) and risk tendencies (e.g., Zimerman, Shalvi & Bereby-Meyer, 2014) might be predictors of dishonest behavior. Most consistently, though, the Honesty-Humility dimension of the HEXACO Model of Personality (Ashton & Lee, 2007) has been linked to dishonest behavior (Heck et al., 2018; Zettler et al., 2019). That is, Zettler et al. (2019) found in their meta-analysis a relation of $\hat{\rho} = -.25$ ($k = 25$, $N = 3{,}073$) between Honesty-Humility and cheating/dishonesty. More specifically, in the above mentioned re-analysis by Heck and colleagues (2018), Honesty-Humility showed a moderate to strong negative effect to dishonest behavior in cheating paradigms. Consequently, individuals low in Honesty-Humility tend to act more dishonest than individuals high in Honesty-Humility.

Irrespective of the direct link between Honesty-Humility and dishonest behavior, Heck and colleagues (2018) pointed at the possibility that Honesty-Humility and p might interact in predicting dishonest behavior. Specifically, Heck et al. (2018) speculated that a higher likelihood of actually winning (i.e., a higher p) "might be especially relevant for individuals who have a general inclination to cheat (i.e., those low in Honesty-Humility): Because these individuals should be motivated to save their face as an honest person (Hilbig, Moshagen & Zettler, 2015), these individuals might particularly consider the probability with which they could, in principle, be exposed as a cheater. In contrast, those high in Honesty-Humility should refrain from lying irrespective of the baseline probability p" (p. 358). Consequently, one might expect an interaction between baseline p and Honesty-Humility such that the cheating rates of individuals low in Honesty-Humility are more strongly affected by p than the cheating rates of individuals high in Honesty-Humility. However, Heck and colleagues (2018) did not find empirical support for this hypothesis. As already mentioned, though, the test by Heck et al. was limited by the fact that the included studies showed a small range of (rather low) ps. Consequently, in Study 2, we not only retested whether lower p is associated with higher dishonesty, but also a potential interaction between p and Honesty-Humility in predicting dishonest behavior in two conditions, namely, one with a high p and one with a low p. Specifically, we tested the following hypotheses:

Hypothesis 1: Participants will cheat more in a condition in which p is high (69,64%) as compared to a condition in which p is low (1,76%).

Hypothesis 2: Participants low in Honesty-Humility will cheat more than participants high in Honesty-Humility.

Hypothesis 3: There will be an interaction between p and Honesty-Humility such that the cheating rates of individuals low in Honesty-Humility are more strongly affected by p than the cheating rates of individuals high in Honesty-Humility.

3 Study 2

3.1 Method

3.1.1 Design, materials, and procedure

Again, we set up an online study using the survey framework formr, recruiting a sample via the survey panel Amazon Mechanical Turk (http://www.mturk.com/. We invited only US residents with an approval rating of 95 or higher. Data were collected at two measurement occasions (T1 and T2) which were two days apart. This was done to avoid any direct influences of the completion of the personality questionnaire on the behavior in the cheating paradigm. At T1, participants received basic information about the study, gave consent to participate, provided some demographic information, and completed the HEXACO-60 (Ashton & Lee, 2009) as well as the Dispositional Greed Scale (DGS; Seuntjens, Zeelenberg, van de Ven & Breugelmans, 2015). Next to the five other basic personality dimensions of the HEXACO model (namely, Emotionality, Extraversion, Agreeableness vs. Anger, Conscientiousness, and Openness to Experience), the HEXACO-60 measures Honesty-Humility. Sample items for Honesty–Humility are "I wouldn't pretend to like someone just to get that person to do favors for me", or "I would never accept a bribe, even if it were very large." The DGS measures dispositional greed and was added to this study from an exploratory point of view to test whether it predicts dishonest behavior (above Honesty-Humility). Sample items are "I always want more", or "One can never have too much money." Responses on both questionnaires were given on a five-point Likert Scale ranging from "strongly disagree" to "strongly agree," and mean factor scores for each participant were computed (by averaging the Likert Scale responses for the 10 Honesty–Humility items and the 7 DGS items, respectively). In order to control for inattentive responding, we interspersed two attention check items in the questionnaires in which participants were asked to choose a certain response category.

At T2, participants worked on the same variant of the coin-toss task as in Study 1. We realized two conditions varying the probability of observing a favorable outcome, low (p = 1.76%) vs high (p = 69.64%). Those values were chosen as they are relatively low and high, and further yielded relatively low (d = .29) and high (d = .64) proportions of dishonest individuals in Study 1. As in Study 1, participants could earn a bonus incentive of $0.75 (next to a flat fee of $1.00; $0.50 for T1 and $0.50 for T2). Participants were informed about p (in their condition), and a corresponding control question was administered at the end of the study.

3.1.2 Analysis plan

The first hypothesis was tested in the MPT framework by restricting the d parameters to be equal across the probability and evaluating the change in the associated G^2 statistic for significance.

To estimate the relation between the proportion of dishonest individuals and Honesty-Humility scores (Hypothesis 2), we applied the modified logistic regression model as proposed in Moshagen and Hilbig (2017) using the RRreg package (Heck & Moshagen, 2018). Given that the modified logistic regression model cannot account for varying baseline probabilities, H3 was again evaluated in the MPT framework by defining parameters reflecting the proportionate change in dishonesty depending on the probability condition ($d_{\text{low}}/d_{\text{high}}$) and testing whether the proportionate change is equal for individuals low and high in Honesty-Humility, thereby adopting a loglinear interaction conceptualization (Kuhlmann et al., 2019).

3.1.3 Participants

We based our sample size calculations on H3 predicting an interaction between the probability of observing a favorable outcome and Honesty-Humility, given that this hypothesis places the highest demands on an appropriate sample size. For the a-priori power analysis (conducted using multitree; Moshagen, 2010), we assumed in the low probability condition a proportion of dishonest individuals of d = .12 and d = .20 for individuals high and low in Honesty-Humility, respectively. In the high probability condition, we assumed d = .15 and d =.80 for individuals high and low in Honesty-Humility, respectively. This represents an interaction between the baseline probability p and Honesty-Humility such that the cheating rates of individuals low in Honesty-Humility are (proportionally) more strongly affected by baseline p than the cheating rates of individuals high in Honesty-Humility. The chosen values correspond to an effect size of Cohen's ω = 0.07 which is considered smaller as a small effect (ω = 0.1, Cohen, 1988).

As in Study 1, participants were randomly assigned to the conditions using predefined allocation ratios, $1/(1-p_i)$. Given α = .05, this resulted in a required sample size of N = 1,480 for a power of $1-\beta$ = .80 to detect the aimed interaction effect. Initially, 2,526 participants completed T1. 70 participants failed to answer at least one of the attention checks correctly and were thus not invited for T2. To reach our required sample size, we opened a batch for 1,650 participants at T2. 1,661 participants completed the coin-toss task at T2. 66 of these failed to answer the control question regarding the objective baseline probability correctly, and were thus excluded. In turn, the final sample size consisted of 1,595 participants, and the sample was relatively heterogeneous with respect to gender (53.10% female, 46.46% male, 0.44% other) and age (M = 36.50, SD = 12.17 years).

3.2 Results

3.2.1 p and dishonest behavior

25.97% of the participants in the low probability condition indicated a win, which is significantly different from the stochastic baseline of 1.76% (Z = 10.49, p < .001). The proportion of dishonest individuals was estimated at d = .25, SE = .02. 85.73% of the participants in the high probability condition indicated a win, which is significantly different from the stochastic baseline of 69.64% (Z = 16.141, p < .001). The proportion of dishonest individuals was estimated to d = .53, SE = .03. In line with Hypothesis 1, the proportion of dishonest individuals was significantly higher in the high probability condition than in the the low probability condition (ΔG^2 (1) = 41.80, p < .001, ω = 0.15).

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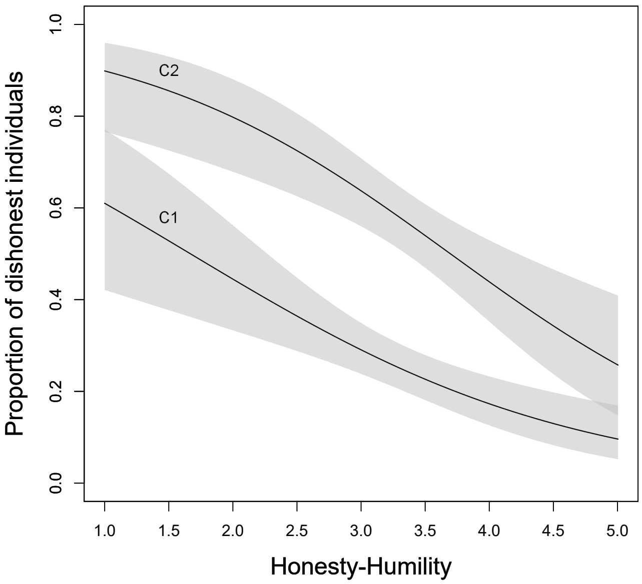

Figure 1: Relations between Honesty-Humility and the proportion of dishonest individuals in the low probability condition (C1) and in the high probability condition (C2) in Study 2.

3.2.2 Honesty-Humility, Dispositional Greed and dishonest behavior

Cronbach's alpha was .79 for Honesty-Humility and .81 for the DGS. Both measures were highly correlated ($r = -.62$, p <.001). In line with Hypothesis 2, a modified logistic regression showed that individuals with lower Honesty-Humility scores were more likely to be dishonest in both the low probability condition (estimate = −0.54, SE = 0.13, Wald test = 16.27, p < .001, OR = 0.58) and the high probability condition (estimate = −0.62, SE = 0.15, Wald test = 16.09, p < .001, OR = 0.54). In contrast, DGS scores did neither predict dishonest behavior in the low probability condition (estimate = 0.14, SE = 0.13, Wald test = 1.19, p = .274, OR = 1.14) nor in the high probability condition (estimate = 0.26, SE = 0.14, Wald test = 3.59, p = .055, OR = 1.29). The result pattern did not change when Honesty-Humility and DGS were simultaneously entered as predictors of dishonest behavior. Honesty-Humility was a significant predictor (low probability condition: estimate = −0.70, SE = 0.17, Wald test = 16.59, p < .001, OR = 0.49; high probability condition: estimate = −0.80, SE = 0.21, Wald test = 14.67, p < .001, OR = 0.45), whereas DGS was not (low probability condition: estimate = −0.26, SE = 0.17, Wald test = 2.37, p = .119, OR = 0.77; high probability condition: estimate = −0.26, SE = 0.20, Wald test = 1.67, p = .188, OR = 0.77).

3.2.3 Honesty-Humility, p, and dishonest behavior

To test Hypothesis 3, a median split on Honesty-Humility (Median = 3.60) was performed in order to obtain two disjoint groups (low Honesty-Humility, high Honesty-Humility), because the standard MPT framework does not allow for interactions between continuous and categorical variables. In line with the analyses above, the low Honesty-Humility group showed a higher proportion of dishonest individuals (d = .32) than the high Honesty-Humility group (d = .19) in the low probability condition (ΔG^2 (1) = 7.64, p = .005, ω = 0.15). Further, the low Honesty-Humility group showed a higher proportion of dishonest individuals (d = .68) than the high Honesty-Humility group (d = .37) in the high probability condition (ΔG^2 (1) = 21.46, p < .001, ω = 0.14). Contrary to Hypothesis 3, however, no significant interaction between p and Honesty-Humility on d was evident (ΔG^2 (1) = 0.07, p = .785, ω = 0.01). In line with this, shrinkage parameters were very similar for the low Honesty-Humility groups ($d_{\text{low}}/d_{\text{high}}$ = .51) and the high- Honesty-Humility groups ($d_{\text{low}}/d_{\text{high}}$ = .47). Relations between Honesty-Humility in both conditions are illustrated in Figure 1.

3.3 Discussion

In contrast to Study 1, we found a significant effect of p on dishonest behavior in Study 2, such that the proportion of dishonest individuals was higher in the condition with higher p. In addition, we replicate previous findings on a relation between Honesty-Humility and dishonest behavior (Heck et al., 2018; Zettler et al., 2019), such that lower levels of Honesty-Humility were linked to a higher proportion of dishonest individuals. In line with Heck et al. (2018), however, we found no signs of a potential interaction between p and Honesty-Humility, even though we considered a condition with a higher p than all studies included in the analysis by Heck et al. (2018). Next, we not only aimed to retest the findings of Study 2, but also set up an experiment avoiding a potential confound between cheating and the distance between the observed and the favorable outcome.

3.4 Baseline probability p and the distance between the observed and the favorable outcome

A study by Hilbig and Hessler (2013) found that in the classic dice-rolling paradigm (Fischbacher & Föllmi-Heusi, 2013) with only one number as the favorable outcome, participants are more likely to cheat when the favorable outcome is set to "3" or "4", compared to "1" or "6". This can be explained by the distance between the observed and the favorable outcome, such that the distance between any of the observed outcomes (therein, any number between "1" and "6") will on average be smaller when "3" or "4" is the favorable outcome, compared to a "1" or "6". Thus, favorable outcomes at the boundary of what can be observed (therein, "1" and "6") provide the least opportunity for relatively small lies as the average of all other outcomes is relatively distant from these favorable outcomes. Importantly, however, the baseline probability p is exactly the same in all of the described conditions (i.e., 1/6).

The distance between the observed and the favorable outcome can have important implications because in some cheating paradigms, such as the one used in Garbarino et al. (2017), p and the distance between the observed and the favorable outcome are confounded, such that the average distance between an observed and the favorable outcome decreases with increasing p. More specifically, Garbarino et al. (2017) used three conditions in which people performed a mind coin tossing game, in which they had to toss a coin three times but before each toss they had to predict which side of the coin will end up face-up. The manipulation used was the number of correct guesses needed to get a financial benefit, such that baseline p was 12.5% (3 correct guesses), 50% (2 or 3 correct guesses), or 87.5% (1, 2 or 3 correct guesses). In this set-up, one does not only manipulate p, but also the average distance between the observed and the favorable outcome. That is, in a condition with high p, a smaller lie is, on average, needed to receive the bonus incentive. Note that this is also the case for the paradigm used in our Studies 1 and 2. For instance, in Study 1, in conditions with high ps, participants needed a small lie only (e.g., having observed four "Heads", but reporting having observed five "Heads") as compared to conditions with rather low p (e.g., having observed four "Heads", but reporting having observed nine "Heads").

Consequently, to disentangle the baseline probability p and the distance between the observed and the favorable outcome, we used a different cheating paradigm in Study 3. In fact, Study 3 conceptually replicates Study 2, but uses a different cheating paradigm to ensure that the influence of p on dishonest behavior is not (only) driven by the distance between the observed and the favorable outcome. Further, we again test a potential interaction between Honesty-Humility and p in predicting the proportion of dishonest individuals. Lastly, to further test the generalizability of the effect of p on the proportion of dishonest individuals, we used a different survey panel with participants from a different country (i.e., UK inhabitants). We tested the same hypotheses as in Study 2.

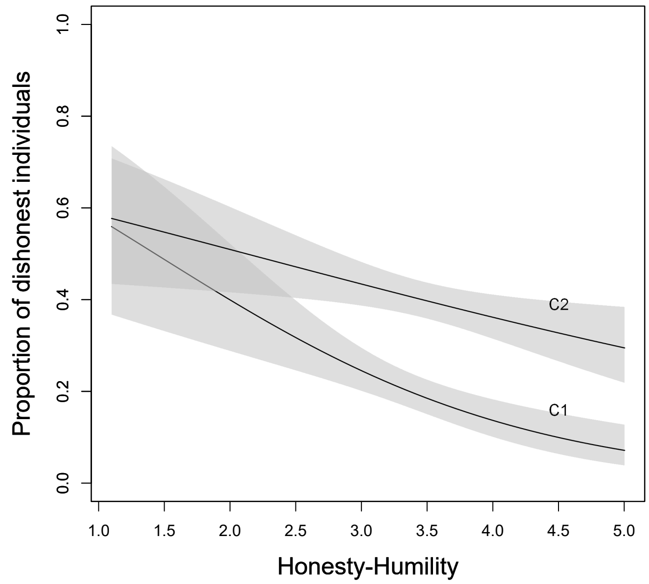

Figure 2: Relations between Honesty-Humility and the proportion of dishonest individuals in the low probability condition (C1) and in the high probability condition (C2) in Study 3.

4 Study 3

4.1 Method

4.1.1 Design, materials, and procedure

Again, we set up an online study using the survey framework formr, this time recruiting a sample via the survey panel Prolific (Palan & Schitter, 2018). We invited only UK residents with a Prolific score of 95 or higher. The study was preregistered on the Open Science Framework (OSF; https://osf.io/b7vzd/). Data were collected at two measurement occasions (T1 and T2), seven days apart. This was done to avoid any direct influences of the completion of the personality questionnaire on the cheating paradigm. At T1, participants received basic information about the study, gave consent to participate, provided some demographic information, and completed the HEXACO-60 (Ashton & Lee, 2009), including one attention check item. At T2, participants worked on a variant of the mind game paradigm (e.g., Jiang, 2013). In detail, participants were displayed a number of text strings with 10 characters length each (e.g., RCVfiPYbnY) and then were asked to write down one of them. Next, a randomly chosen text string was displayed and participants were asked whether the displayed text string matched the text string they wrote down beforehand. Importantly, in addition to their flat-fee for participation (T1 = £ 0.55, T2 = £ 0.40), participants received a bonus incentive of £ 0.40 when reporting that the target text string they wrote down and the displayed text string matched. Consequently, participants had the opportunity to cheat in order to obtain the bonus incentive by reporting that the text strings matched even if they did not. Importantly, unlike in the paradigms used in Study 1 and Study 2, the distance between the observed and the favorable outcome should not play a role in this paradigm (as there is no objective distance between text strings as compared to that there is an objective distance between the number of observed and the number of heads needed for the favorable outcome).

We varied the probability of observing a favorable outcome, namely, low (p = 2%) vs. high (p = 50%) for each participant. In detail, participants were displayed 50 text strings in the low probability condition (i.e., p = 2%) and two text strings in the high probability condition (i.e., p = 50%). p values were chosen to approximately reflect the conditions in Study 2, while allowing for simplicity of the cheating paradigm (i.e., p = 50% was implemented by displaying two strings only) and feasibility (e.g., overall expenses for paying participants) of the study.

4.1.2 Participants

An a priori power analysis was conducted using multitree (Moshagen, 2010). The approach was the same as for Study 2, but more conservative values for d were chosen, and it was aimed for a higher power. Specifically, in the low probability condition we assumed d = .105 for individuals with high Honesty-Humility scores and d = .20 for individuals with low Honesty-Humility scores. Further, in the high probability condition we assumed d = .15 for individuals with high Honesty-Humility scores and d = .80 for individuals with low Honesty-Humility scores. The above sketched setup corresponds to an effect size of Cohen's ω = 0.06.

Quotas for each condition were then defined by 1:4 (C1:C4) to ensure that more participants were assigned to the condition (C1) in which cheating was more unlikely. Given α = .05, this resulted in a required sample size of N = 2,554 for a power of $1 - \beta$ = .90 to detect such an interaction effect.[5] Aiming to oversample at the first measurement occasion, initially 3,070 participants completed T1. 32 participants did fail to answer at least one of the attention checks correctly and were thus not invited for T2. 2,813 participants completed the mind game task at T2. 165 of these failed to answer the control question regarding the objective baseline probability (in their condition) correctly. Thus, the final sample size consisted of 2,648 participants which were relatively heterogeneous with respect to gender (67.03% female, 32.66% male, 0.30% other) and age (M = 36.33, SD = 13.13 years).

[5]This sample size calculation differs from the one reported in the preregistration due to a copy and paste mistake (a prior sample size calculation for two main effects, instead of an interaction, was copied from the multitree output window).

4.2 Results

4.2.1 p and dishonest behavior

21.39% of the participants in the low probability condition indicated a win, which is significantly different from the stochastic baseline of 1.76% (Z = 10.61, p < .001). The proportion of dishonest individuals was estimated at d = .20 (SE = .02). 69.81% of the participants in the high probability condition indicated a win, which is significantly different from the stochastic baseline of 50% (Z = 19.970, p < .001). The proportion of dishonest individuals was estimated to d = .40, SE = .02. In line with Hypothesis 1, the proportion of dishonest individuals was significantly higher in the high probability condition (ΔG^2 (1) = 47.52, p < .001, ω = 0.13) as compared to the low probability condition.

4.2.2 Honesty-Humility and dishonest behavior

Cronbach's alpha was .75 for Honesty-Humility. In line with Hypothesis 2, modified logistic regressions showed that individuals with lower Honesty-Humility scores were more likely to be dishonest in both the low probability condition (estimate = −0.50, SE = 0.12, Wald test = 16.77, p < .001, OR = 0.61) and the high probability condition (estimate = −0.21, SE = 0.08, Wald test = 6.40, p = .011, OR = 0.81).

4.2.3 Honesty-Humility, p, and dishonest behavior

To test Hypothesis 3, we again performed a median split on Honesty-Humility ($Median$ = 3.60) in order to obtain two disjoint groups (low Honesty-Humility, high Honesty-Humility). The low Honesty-Humility group showed a higher proportion of dishonest individuals (d = .13) than the high Honesty-Humility group (d = .26) in the low probability condition (ΔG^2 (1) = 11.48, p < .001, ω = 0.16). Further, the low Honesty-Humility group showed a higher proportion of dishonest individuals (d = .34) than the high Honesty-Humility group (d = .44) in the high probability condition (ΔG^2 (1) = 5.80, p = .008, ω=0.05). However, and contrary to Hypothesis 3, we found no significant interaction between p and Honesty-Humility on d (ΔG^2 (1) = 3.34, p = .068, ω = 0.037). In line with this result, shrinkage parameters were, descriptively, even higher for the low Honesty-Humility groups ($d_{\text{low}}/d_{\text{high}}$ = .60) than for the high-Honesty-Humility groups ($d_{\text{low}}/d_{\text{high}}$ = .39). Relations between Honesty-Humility and dishonesty in both conditions are illustrated in Figure 2.

4.3 Discussion

We found significant effects of p and Honesty-Humility on dishonest behavior, extending the findings of Study 1 and Study 2. In line with Heck et al. (2018) as well as Study 2, we found no signs of an interaction between p and Honesty-

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Humility. Further, by using a different paradigm with text strings as compared to numbers, we disentangled the effect of p from the effect of the distance between the observed and the favorable outcome.

5 General discussion

This investigation provides evidence for effects of a situation factor, the baseline probability p of observing a favorable outcome, and a person factor, Honesty-Humility, on dishonest behavior. The results suggest that both factors have an independent influence on dishonest behavior such that higher p (though in our Study 1 only descriptively, not statistically) and lower Honesty-Humility (only investigated in Studies 2 and 3 herein) are linked to higher probabilities of dishonest behavior. Importantly, Study 3 provides evidence that disentangles an effect of p from an effect of the distance between the observed and the favorable outcome. Contrary to our expectations and findings from studies investigating criteria other than cheating (e.g., Zettler & Hilbig, 2010), there was no evidence for a person-situation interaction between p and Honesty-Humility in predicting dishonest behavior.

Overall, the results provide novel insights into how humans perceive and act in situations that allow for dishonest behavior. Indeed, information about the likelihood of an event (in terms of observing a favorable outcome) is used and integrated in peoples' decision-making process on whether to cheat or not. Specifically, a lower likelihood of observing a favorable outcome was related to lower rates of dishonest behavior. Based on previous theorizing and evidence, a plausible explanation for this pattern is that unlikely events do not allow maintaining a somewhat positive and honest perception of oneself as well as by others, because behavior might more likely be questioned (by others) when it seems less likely overall. Relatedly, reporting a favorable outcome when the corresponding probability is very low might threaten participants' anonymity (because this might make them look suspicious – and when the probability is 0, others even know that they cheated), and, in turn, entail a higher risk for punishment.

It should be mentioned that the relation between p and dishonest behavior, although in the expected direction, was not found to be statistically significant in Study 1. However, from our perspective, this was likely due to a lack of power as suggested by the consistent findings across the well-powered Studies 2 and 3, as well as similar effect sizes across all three studies (i.e., $\omega = 0.10$, 0.15, and 0.13, respectively).

Although this investigation also replicated the effect of Honesty-Humility on dishonest behavior (e.g., Heck et al., 2018), the predicted interaction between p and Honesty-Humility on dishonest behavior was not confirmed. This suggests that, independent of their trait level on Honesty-Humility, individuals are equally sensitive towards p. Importantly, this is in contrast to previous studies that have found Honesty-Humility to interact with situation factors in predicting behavior. For example, Honesty-Humility was found to interact with the presence and absence of moral cues in predicting dishonest behavior (Kleinlogel et al., 2018), with the fear of retaliation in predicting fairness (Hilbig & Zettler, 2009), or with (perceptions of) organizational factors in predicting counterproductive work behavior and other organizational outcomes (Chirumbolo, 2015; Wendler, Liu & Zettler, 2018; Wiltshire, Bourdage, Lee, 2014; Zettler & Hilbig, 2010). On the other hand, there are at least three other studies that also failed to find interaction effects between situation factors and Honesty-Humility, (Allgaier et al., 2019; De Vries & van Gelder, 2015; Hilbig & Zettler, 2015) suggesting that more research on the exact conditions when trait Honesty-Humility and situation factors interact with each other is needed from a more general level.

This study might also serve as a toe-hold for researchers when designing experiments. In line with Garbarino et al. (2018), it provides evidence that p (in terms of the probability to observe a favorable outcome; or, more generally, to win rightfully), as present in multiple different cheating paradigms, has a direct influence on the to be expected rates of dishonest behavior. Further, within the same paradigm, different ps will lead to significant differences in observed dishonesty rates. Thus, p should definitely be considered when planning and sampling studies on dishonest behavior. For example, researchers might estimate adequate sample sizes by considering their cheating paradigm, the corresponding p, and expected cheating rates in power analyses (see also Moshagen & Hilbig, 2017).

Several limitations should also be considered. Whereas our studies relied on objective likelihoods (i.e., it was clearly defined and communicated to participants how likely a win is), many real life scenarios might come with more uncertainty, and how likely an event is might be hard or impossible to estimate. For instance, it might be that – especially in real-life scenarios – peoples' subjective probability of observing a favorable outcome is more relevant that the objective probability (if this can be estimated at all). Future research might thus aim to investigate whether, and, if so, how certainty of likelihoods and ratability influence dishonest behavior.

Further, it is important to note that this investigation did purely rely on scenarios in which participants did not have to fear severe negative social consequences of their dishonest behavior. That is, the participants did act dishonest towards researchers whom they do not know personally and who themselves have no identifying information about the participants in a one-shot interaction. Indeed, recent meta-analytical findings suggest that underlying decision-making processes with regard to cheating or not differ when abstract entities, as compared to more concrete ones, are harmed by dishonesty (Köbis et al., 2019). Also, there was no potential monitoring and, in turn, punishment (except for not obtaining a bonus incentive) for cheaters. In contrast, in real life people often interact with others more frequently, so that repeatedly reporting unlikely events might lead to negative social consequences such as reputation losses. Further, cheating in real life can entail negative consequences (e.g., paying a fine) when being caught. Thus, the effect of p might be stronger in scenarios with repeated interaction and more severe negative consequences. The mentioned aspects of potential subjective probabilities (even in our studies), dealing with abstract entities, as well as no severe punishment might have outruled a potential interaction effect between Honesty-Humility and p in order investigation – which should be investigated in future studies.

5.1 Conclusion

This investigation aimed to further facilitate research on and understanding of the influence of a situation factor, the baseline probability p of observing a favorable outcome, and a person factor, Honesty-Humility, on dishonesty. In addition, a potential interaction between both factors in predicting dishonesty was tested. While the first study find no significant relation between p and dishonesty, arguably because the study was underpowered, the second and third study provide evidence for two independent main effects – in contrast to an interaction – of p and Honestly-Humility. Herein, higher p and lower levels of Honesty-Humility were linked to more dishonest behavior.

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