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Not all computerized cheating tasks are equal: A comparison of computerized and non-computerized versions of a cheating task

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ABSTRACT

Computerized versions of population inferred cheating tasks (C-PICT)—i.e., tasks in which dishonesty is statistically determined on the aggregate by comparing self-reported outcomes with a known probability distribution—have become increasingly popular. To this date no study has investigated whether non-computerized population inferred cheating tasks (PICT) and C-PICT as well as different implementations of C-PICT produce similar results. The current study tackles both issues via a well-powered pre-registered online experiment (N = 3,645) with four conditions. Participants played either a non-computerized coin toss task (CTT) (C1) or one of three computerized CTT: a computerized CTT provided via an external website (C2), a computerized CTT provided within the survey framework of the study in which participants were explicitly informed that the actual outcome of the CTT was not monitored (C3), or a computerized CTT provided within the survey framework of the study in which participants were explicitly informed that the actual outcome of the CTT was monitored (C4). A priori we expected the probability of dishonesty to be higher in C1 compared to C2, C3, and C4, as well as lower in C4 compared to C3 and C2. Results show that the probability of dishonesty is higher in C1 and C2 compared to C3 and C4. Conversely, no significant difference was observed between C1 and C2, nor between C3 and C4. Taken together, our results indicate that C-PICT produce results similar to PICT when they are provided via an external website, but not when they are implemented within the survey framework of the study.

1. Introduction

Dishonesty imposes a heavy burden on societies at large. Every year billions of dollars are lost to societies due to fraud (Gee & Button, 2019), money laundering, and corruption (United Nations, 2018, 2019). In light of the societal costs it is not surprising that scholars have investigated the antecedents, correlates, and consequences of dishonesty.

In recent years, one important stream of dishonesty research has relied on experimental paradigms and so-called population inferred cheating tasks (PICT) in particular (Abeler, Nosenzo, & Raymond, 2019; Gerlach, Teodorescu, & Hertwig, 2019; Jacobsen, Fosgaard, & Pascual-Ezama, 2018). In these tasks, the occurrence and extent of dishonesty is statistically determined on the aggregate level by comparing self-reported outcomes with a known probability distribution. Examples of PICT include the coin toss task (CTT; Bucciol & Piovesan, 2011) and die roll task (DRT; Fischbacher & Föllmi-Heusi, 2013). Common to these tasks is that participants have an opportunity to profit from misreporting information obtained in private, such as the outcome of one or several coin toss/es or die roll/s. The incentive structure is typically set up so that participants receive a payoff if they report a specific outcome (e.g., rolling a

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six), or in an incremental fashion so that some outcomes lead to higher payoffs (e.g., rolling a six results in a higher payoff than rolling a five etc.). An important aspect of PICT is that participants enjoy full anonymity, providing them with a strong sense of privacy. Highlighting the importance of this aspect, studies have shown that people lie less if their sense of privacy is compromised. In a Registered Report by Schild, Heck, Ścigała, and Zettler (2019), for instance, the probability of dishonesty dropped from 0.28 to 0.11 when monitoring (i.e., the experimenter knows the actual outcome and could compare it to the reported outcome) was introduced. Similarly, Gneezy, Kajackaite, and Sobel (2018) found monitoring to reduce the overall level of dishonesty, and Kajackaite and Gneezy (2017) observed an increase in dishonesty when all concerns for observability were alleviated. Finally, in a recent meta-study Abeler et al. (2019) uncovered a similar pattern and concluded that both a preference for being honest and a preference for being seen as honest are the primary drivers of truth-telling.

Whereas many studies have administered PICT in a lab using actual coins, dice, or the like (Abeler et al., 2019; Gerlach et al., 2019; Jacobsen et al., 2018), more and more studies have started to implement computerized versions of these tasks (C-PICT). Broadly speaking, C-PICT are typically implemented using one of two approaches. In the first approach, the C-PICT is implemented into an existing survey framework under the clear umbrella of the study environment (which we term *internal implementation*). This includes the presentation of C-PICT on lab computers or online surveys under the header of the experimenter's lab or university (e.g., Gross, Leib, Offerman, & Shalvi, 2018; Hermann & Mußhoff, 2019; Kocher, Schudy, & Spantig, 2018). In the second approach, the C-PICT is implemented via links to an external website (which we term *external implementation*) which is either owned by the researchers or by some third party such as https://justflipacoin.com/ or https://www.random.org/ (e.g., Balasubramanian, Bennett, & Pierce, 2017; Chou, 2015; Duncan & Li, 2018).

Although C-PICT comes with certain benefits, such as high flexibility (e.g., the probability of different outcomes can be manipulated), tighter experimental control (e.g., the number of possible coin tosses or die rolls can be fixed), as well as easy implementation of overt and covert monitoring, there might be important caveats in using C-PICT. In particular, C-PICT might not provide the same felt sense of privacy for the participants as non-computerized PICT for the very reason that it is easy to implement overt and covert monitoring. This applies to both external C-PICT which can be monitored using session recording software (e.g., Hotjar or Inspectlet), insofar the external website is owned by the researchers, as well as internal C-PICT which can easily be coded to record the true outcome of each coin toss or die roll. As such, it seems likely that participants would experience a diminished sense of privacy when playing a C-PICT, as they might correctly assume that it is possible to monitor the truthfulness of their reports. Moreover, it could be that internal C-PICT do not provide the same sense of privacy as external C-PICT, because participants can infer that the former, but not necessarily the latter is provided by the researchers, increasing the likelihood that participants feel monitored in internal C-PICT even if they are not. Given that people lie less if their sense of privacy has been compromised (Abeler et al., 2019; Gneezy et al., 2018; Kajackaite & Gneezy, 2017; Schild et al., 2019), it could be that PICT and C-PICT, as well as different implementations of C-PICT (i.e., internal vs. external), do not produce similar results. Given the increasing use of C-PICT (in the light of their potential benefits), it is crucial to explore if this is the case.

2. Method

2.1. Procedure

To investigate this question, an online experiment with four conditions was set up in formr (Arslan, Walther, & Tata, 2020; for an overview, see Table 1). In the first condition (C1), participants played a non-computerized CTT as used by Zettler, Hilbig, Moshagen, and de Vries (2015). Here, participants were simply asked to toss a real coin twice and report the outcome in private. If a participant reported tossing two heads in a row, the participant received a payoff of £0.40. In the second, third and fourth condition, participants played differently implemented computerized CTT. Specifically, participants in C2 played an external computerized CTT provided via a third-party website (https://justflipacoin.com). In C3 participants played an internal unmonitored computerized CTT provided by us within the survey framework of this study (i.e., we/our software did not record the actual outcome of the CTT). Finally, participants in C4 played an internal monitored computerized CTT also provided by us under the clear umbrella of the study environment (i.e., we/our software did record the actual outcome of the CTT). Participants in C2 and C3 were made explicitly aware that the outcome of the coin tosses were not being monitored, whereas participants in C4 were informed that the outcome of the coin tosses were monitored. Additionally, participants in C4 were ensured that the fact that they were being monitored would not affect their final payment in any way (i.e., they would not lose their incentive payment when cheating). The implementation of monitoring in C4 was done in order to be able to assess the impact of using an internal (C3) versus external (C2) C-PICT on peoples' willingness to lie, relative to the effect of overt monitoring (C4). All experimental instructions are provided in the Supplementary Material 1. Based on the existing literature the following pre-registered hypotheses were stated (https://osf.io/hjnxb/):

Hypothesis 1:

- People will cheat more when playing a non-computerized version of the coin toss task as compared to any of the computerized versions of this task.

Hypothesis 2:

- People will cheat less when they are told that they are being monitored while playing a computerized version of the coin toss task compared to when they are told that they are not being monitored while playing a computerized version of the coin toss task.

Table 1
Overview of the experimental conditions.

	C1	C2	C3	C4
Type of coin:	Real	Computerized	Computerized	Computerized
Monitoring implemented:	No	No	No	Yes
Monitoring possible in principle:	No	Yes	Yes	Yes
Coin toss generated by software provided by the researchers:	No	No	Yes	Yes
Implementation method:	Standard –Participants tossed a coin of their own	External –Participants were redirected to a third-party website with a computerized coin	Internal – Participants were provided with a computerized coin within the survey framework of the study	Internal –Participants were provided with a computerized coin within the survey framework of the study

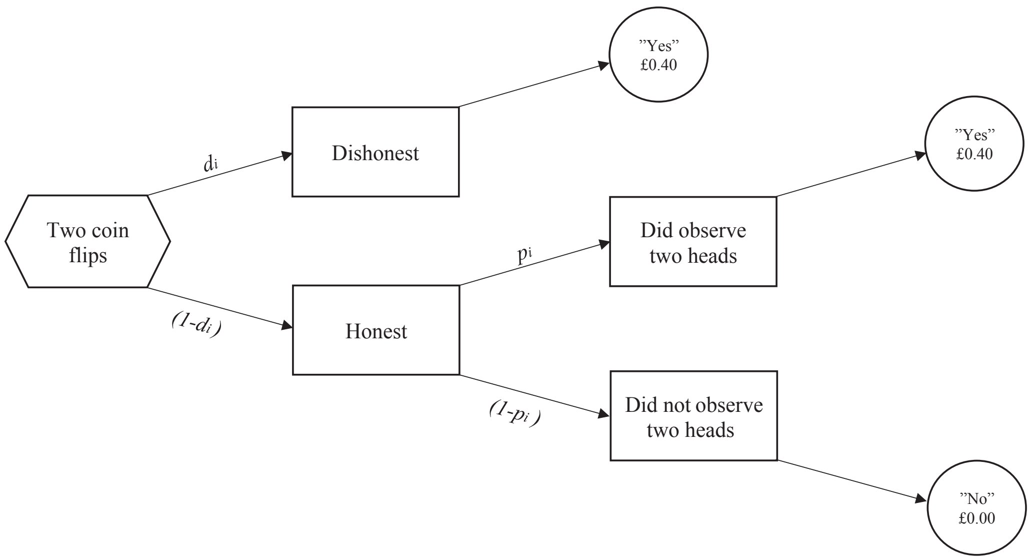

Fig. 1. Illustration of the basic multinomial processing tree model underlying the analyses.

2.2. Analytic framework

An important feature of the CTT is that the proportion of alleged "wins" is conflated with legitimate "wins", precluding the immediate interpretations of reported "wins" as an indicator of dishonesty (Moshagen & Hilbig, 2017). However, given that the baseline probability p for legitimate "wins" is known one can estimate the probability of dishonesty given the following assumptions: (1) dishonest respondents always claim to have won, (2) honest respondents only report to have won when this is actually the case, and (3) respondents never lie to their disadvantage by denying to have won. Given these assumptions, the proportion of alleged "wins" is a function of the proportion of honest and dishonest respondents and the baseline probability p such that:

$$p(\text{win}) = d + (1 - d) * p, \tag{1}$$

where d denotes the proportion of dishonest respondents (Moshagen & Hilbig, 2017). Solving for d

$$d = \frac{p(\text{win}) - p}{(1 - p)}, \tag{2}$$

one can obtain an estimate of the proportion of dishonest respondents by replacing $p(win)$ with the observed proportion of reported wins (q). In order to estimate d along with its standard error, and, more importantly, to allow for pairwise comparisons of the probability of dishonesty between conditions, we relied on a multinomial processing tree (MPT) model (Moshagen, 2010). An illustration of the basic MPT model used is provided in Fig. 1.

2.3. Power analysis

In order to estimate an appropriate sample size for testing our hypotheses, we first looked at previous studies utilizing non-computerized versions of the CTT. Based on a recent meta-analysis (Gerlach et al., 2019), we expected the probability of dishonesty for the non-computerized CTT to be approximately 0.32. Second, we ran a pilot study via Prolific (N = 121) to estimate how much people cheat when playing an external unmonitored (i.e., C2; N = 53, 74% female, 2% other) versus an internal monitored computerized (i.e., C4; N = 68, 68% female, 1% other) CTT. These two conditions were chosen because they were expected to produce results most and least similar to the non-computerized CTT. The experimental procedure of the pilot study mirrored that of the full experiment except that the participants were paid £0.50 for reporting tossing two heads instead of £0.40 (in the full experiment). Relying on our analytical framework, the probability of dishonesty in the pilot study was estimated to be 0.20 in C2 and 0.06 in C4 using multiTree version 0.46 (Moshagen, 2010).

Based on these findings we conducted an a-priori power analysis. Therein, the expected proportion of dishonest individuals d was set to d_1 = 0.32 for C1, $d_{2,3}$ = 0.20 for C2 and C3, and d_4 = 0.06 for C4. Using these values, Cohen's ω was estimated to be ω > 0.07 for the pairwise comparisons between C1 and C2, C3 as well as C4 (i.e., $d_1 = d_{2,3,4}$; Hypothesis 1). Similarly, Cohen's ω was estimated to be ω > 0.09 for the pairwise comparisons between C4 and both C2 and C3 (i.e., $d_4 = d_{2,3}$; Hypothesis 2). Aiming for the most conservative model (i.e., $d_1 = d_{2,3}$ with d_4 freely estimated; Cohen's ω = 0.07) and high statistical power (i.e., 1-β = 0.95, α = 0.05) the sample needed for this study was estimated to be N = 3,220. Oversampling slightly, we aimed to recruit 3,400 participants.

Given that not all devices or web browsers fully support animated content and the fact that technical issues can arise during online experiments, we expected that at least some participants would experience technical problems. To address this issue, we invited

3,650 participants to the experiment thereby ensuring that we would reach our aim of 3,400 participants not experiencing any severe technical problems. Moreover, to make sure that all participants included in the final sample were able to see the computerized coin toss and did not experience any severe technical issues we asked participants to report a specific number presented on an animated coin, as well as to report whether they experienced any technical problems at the end of the experiment.[1]

2.4. Participants

Participants from Australia, Canada, New Zealand, UK and the US were recruited via Prolific (prolific.co; Palan & Schitter, 2018). Only Prolific users with an approval rating of 95 or above were allowed to participate. Among the final sample of 3,645 participants,[2] $n = 2{,}185$ reported to be female, $n = 1{,}426$ to be male, and $n = 34$ categorized their gender as "other". Participants' age ranged from 18 to 78 ($M = 35.52$, $SD = 12.03$) years. Participants were paid £0.40 as a participation fee, and could win another £0.40 in the CTT.

2.5. Data analysis

The probability of dishonesty per condition was estimated using our analytical framework. The unconstrained baseline model involved four distinct free parameters for d (d_1, d_2, d_3, and d_4) and two fixed baseline probabilities ($p_1 = 0.25$ and $p_2 = 0.00$). The first baseline probability, p_1 (i.e., the probability of tossing two heads in a row), was used to estimate d_1, d_2, and d_3, whereas the second, p_2, was used to estimate d_4 because the actual number of dishonest participants was known in C4. To estimate the probability of dishonesty in C4 it was thus necessary to exclude all participants who actually won, because these participants did not have an incentive to lie. Furthermore, in C4 it was necessary to set the baseline probability to $p_2 = 0.00$, ensuring that participants who falsely claimed to have won would be classified as dishonest.[3] These specifications resulted in a saturated baseline model with $G^2(0) = 0$. In order to test whether the estimated parameters for d differed from zero, the baseline model was compared against four restricted models in which each of the parameters was constrained to zero. Finally, pairwise comparisons between the estimated probability of dishonesty across all four conditions were performed by comparing the unconstrained baseline model against six restricted models in which two of the parameters were constrained to equality (i.e., $d_1 = d_{2,3,4}$; $d_2 = d_3$; $d_{2,3} = d_4$). All statistical analyses were performed using R version 3.5.1 (R Core Team, 2017) and multiTree version 0.46 (Moshagen, 2010). Scripts and data files to replicate all analyses are available via https://osf.io/z59my/.

3. Results

Exact demographics can be found in the Supplementary Material 2 (Table S1). No differences were observed between conditions with regard to age (F (3, 3641) $= 0.13$, $p = 0.944$), gender ($X^2(6) = 3.16$, $p = 0.788$), and education ($X^2(12) = 20.95$, $p = 0.051$). The probability of dishonesty, $\hat{d}$, was estimated to be 0.18, 0.14, 0.06 and 0.05 in C1, C2, C3, and C4, respectively (Fig. 2). Thus, dishonesty was observed in all four conditions with estimates of d significantly differing from zero (all $p < 0.01$). Pairwise comparisons of the estimated probability of dishonesty revealed significant differences between C1 and C3 ($\Delta G^2(1) = 17.95$, $p < 0.001$, $\omega = 0.07$), C1 and C4 ($\Delta G^2(1) = 30.93$, $p < 0.001$, $\omega = 0.10$), C2 and C3 ($\Delta G^2(1) = 7.67$, $p = 0.006$, $\omega = 0.05$), as well as C2 and C4 ($\Delta G^2(1) = 13.28$, $p < 0.001$, $\omega = 0.06$). Conversely, no significant differences were observed between C1 and C2 ($\Delta G^2(1) = 1.81$, $p = 0.178$, $\omega = 0.02$) as well as between C3 and C4 ($\Delta G^2(1) = 0.02$, $p = 0.877$, $\omega = 0.00$).[4] Overall, these results partially support Hypotheses 1 and 2. Specifically, Hypothesis 1 was supported by the result that participants who played an internal computerized CTT with or without monitoring (C3 and C4) were less likely to lie compared to participants who played a non-computerized CTT (C1). Hypothesis 2 was supported by the result that participants who were explicitly monitored while playing an internal computerized CTT (C4) cheated less than participants who played an external computerized CTT without being monitored (C2). Opposite to what was predicted, there were no significant differences between the external computerized CTT (C2) and the non-computerized version of this task (C1), as well as between the internal computerized CTT with (C4) or without monitoring (C3).

[1] Indeed, prior to this study we ran an identical study ($N = 3{,}544$) in which a substantial number of participants in C3 and C4 contacted us via Prolific and informed us that they had experienced technical issues with the computerized CTT, so that this data had to be discarded. To insure against this in the current study, we not only fixed the reason for this technical error but also implemented a computerized coin toss check after the actual task in which participants were asked to report a specific number presented on an animated coin. Moreover, we asked all participants to report whether they experienced any technical problems at the end of the experiment. The probability of dishonesty for C1 ($N = 867$) and C2 ($N = 872$), $\hat{d}$, from this prior study was estimated to be 0.15 and 0.17, respectively. As in the current study, no significant difference was observed between C1 and C2 ($\Delta G^2(1) = 0.49$, $p = .483$, $\omega = 0.02$; see Supplementary Material 2).

[2] 3,772 participants started the experiment but only 3,673 finished. Of these, 28 where excluded because they reported experiencing severe technical issues during the experiment, leading to a final sample of N = 3,645.

[3] An alternative, although less accurate, way to analyze the data is to treat C4 as the other conditions pretending not to know which participants lied. Treating C4 as the other conditions does not change the results and leads to the same overall conclusions (see Supplementary Material 2).

[4] To check the robustness of these results, non-parametric analyses were conducted. These produced similar results and do not change the overall conclusions from this study (see Supplementary Material 2).

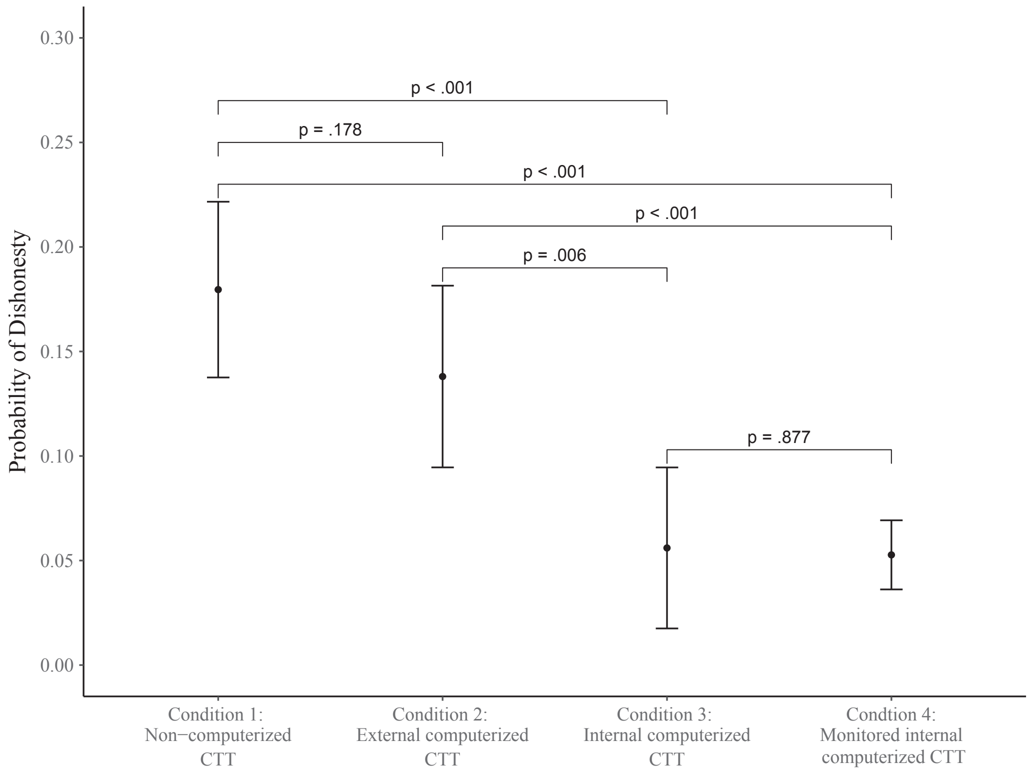

Fig. 2. Estimated probability of dishonesty per condition with 95% CI.

4. Discussion

The present study provides strong evidence that not all C-PICT are equal. Specifically, C-PICT only appear to produce similar results to their non-computerized counterparts when they are implemented externally. One possible explanation for this is that participants experience a diminished sense of privacy when playing an internal as compared to an external C-PICT. That is, participants might be more inclined to believe that they are being monitored when playing an internal C-PICT, arguably because they can infer that the C-PICT is provided by the experimenters, and that it is easy to monitor the truthfulness of their reports. In support of this explanation, no significant difference was observed between C4 and C3, in which the computerized CTT was internally implemented with or without monitoring, indicating that participants in both conditions were under the impression that they were being monitored, even though this was not the case (in C3). Overall, this interpretation is in line with the existing literature which suggests that people are very concerned with the reputational costs of being perceived as dishonest, creating a strong preference for truth-telling when people know or think that they are being monitored (Abeler et al., 2019; Gneezy et al., 2018; Kajackaite & Gneezy, 2017; Schild et al., 2019).

In the light of these results, researchers should thoroughly consider the implications of using internal C-PICT, as this implementation method significantly alters participants' willingness to cheat. By not taking this into account, researchers' run into the risk of underestimating the probability of dishonesty, with respect to the specific sample, incentive structure, and experimental intervention. On the other hand, finding effects when using internal C-PICT could be taken as strong evidence that specific interventions are highly effective in mitigating dishonesty, because internal implementation in itself strongly reduces misreporting and possibly crowds out (most of) the impact of interventions with only small effects. In sum, one should be cautious when drawing conclusions across studies utilizing internal and external C-PICT, as the results from any single study might be influenced by the method of implementation used.

Although the current study provides strong evidence that not all C-PICT are equal, some limitations should be acknowledged. First, the current study was conducted online as it would have been difficult to reach the required sample size without using an online crowdworking platform such as Prolific. For this reason, it is not clear whether the same pattern of results would emerge in a lab setting. For instance, it could be that participants lie less when playing C-PICT on lab-computers irrespective of the method of implementation, given that (software on) lab-computers are very easy to monitor and, in most cases, provided by the researchers themselves. Second, based on the current study it is not possible to determine exactly why participants lie less when playing an internal C-PICT, although the explanation provided above seems plausible. Future research should therefore investigate this further, possibly by asking participants to report their felt sense of privacy while playing either an internal or external C-PICT. In addition to investigating why people lie less when playing an internal C-PICT, another avenue for future research could be to explore what differentiate those who are sensitive to how C-PICTs are implemented, and adapt their behavior accordingly, compared to those who are not. Finally, the PICT used in this study did not allow for partial lying. Given that a larger fraction of people seems to lie partially when they have full anonymity compared to when they do not (Gneezy et al., 2018), future studies might test whether more participants lie partially in external as compared to internal C-PICT.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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