# When the Eyes Say Buy: Visual Fixations during Hypothetical Consumer Choice Improve Prediction of Actual Purchases

Taisuke Imai Min Jeong Kang Colin F. Camerer *

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**Abstract**

Consumers typically overstate their intentions to purchase products, compared to actual rates of purchases, a pattern called "hypothetical bias". In laboratory choice experiments, we measure participants' visual attention using mousetracking or eye-tracking, while they make hypothetical as well as real purchase decisions. We find that participants spent more time looking both at price and product image prior to making a real "buy" decision than making a real "don't buy" decision. We demonstrate that including such information about visual attention improves prediction of real buy decisions. This improvement is evident, although small in magnitude, using mousetracking data, but is not evident using eye-tracking data.

JEL Code: D12, D90, C91

Keywords: mousetracking; eye-tracking; hypothetical bias; prediction

*Imai: Corresponding author. Ludwig Maximilian University of Munich, Munich, Germany. taisuke.imai@econ.lmu.de. +49 (0)89-2180-2107. ORCID 0000-0002-0610-8093. Kang: California Institute of Technology, Pasadena, CA, USA. kang@hss.caltech.edu. Camerer: California Institute of Technology, Pasadena, CA, USA. camerer@hss.caltech.edu. ORCID 0000-0003-4049-1871. This paper is based on part of Ph.D. dissertation of Taisuke Imai. Authors thank Daw-An Wu and Rahul Bhui for their help with data collection and analysis. This work was supported by the Gordon and Betty Moore Foundation. Imai acknowledges financial support from the Nakajima Foundation and Deutsche Forschungsgemeinschaft through CRC TRR 190.

# 1 Introduction

Real choices are binding consequential commitments to a course of action. Scientists and policy makers who are interested in real choices, however, often rely on hypothetical statements about what people *would* choose, rather than what they *do* actually choose. Measurement of hypothetical choice is common in many fields and is usually done for practical reasons. Examples include pre-election polling, marketing surveys of new products for sales forecasting (Green and Srinivasan, 1990; Jamieson and Bass, 1989; Silk and Urban, 1978), artificial choices about moral dilemmas or measurement of "sacred" values, which cannot be enforced for ethical reasons (Berns et al., 2012; FeldmanHall et al., 2012), and surveys used to estimate dollar value of goods that are not traded in markets (such as clean air or the prevention of oil spills) for cost-benefit analysis (Carson and Hanemann, 2005; Shogren, 2005).

The maintained assumption in all these research areas is that hypothetical choices offer some useful relation to real choices. However, many comparisons show that hypothetical and real choices can differ systematically, generating differences that are collectively called "hypothetical bias". Typically, hypothetical bias is an upward "yes bias": people overstate their intentions to buy new products and vote, compared to actual rates of purchase and voting (Cummings et al., 1995; List and Gallet, 2001; Little and Berrens, 2004; Murphy et al., 2005).

Given the possibility of hypothetical bias, an important practical challenge is how to accurately forecast real choices from data on hypothetical choices. Many studies have explored different experimental or statistical procedures that might reduce bias (reviewed in online appendix F). Another approach that has been explored more recently is to measure psychological or neural variables that are recorded during the process of hypothetical choice and use those measures to forecast actual choice. Since these measures often *precede* choice, we generally call them "pre-choice" measures. We report new evidence from this approach using measures of visual attention.

We hypothesize that what people look at during the hypothetical choice will help forecast whether they will stick with their original choice, or will change their minds when making a subsequent real choice. This is motivated by recent empirical evidence and computational models that suggest a close link between choice behavior and visual attention (Krajbich et al., 2010;

Krajbich and Rangel, 2011; Krajbich et al., 2012). We recorded visual attention as people made hypothetical choices about consumer products. They were later "surprised" by the opportunity to actually buy some of those same products. This design allows us to measure visual attention associated with hypothetical bias.

Furthermore, using both mousetracking and eye-tracking, we can compare the quality and informational content of visual attention measured with these two techniques and assess their practical usefulness. [1]

The main result is the following: during hypothetical choice, the more people looked at prices, and the longer they took to transition from looking to making a choice, the more likely they were to switch a hypothetical "buy" to a real "don't buy". That is, visual attention measured during hypothetical choices improves prediction in real purchase decisions. This improvement in prediction is not large in magnitude and evident only in mousetracking data, but it provides initial evidence that some improvement is possible using pre-choice measures. It is likely that larger samples and more pre-choice measures, building on our findings, could provide a bigger improvement in predicting real purchases from hypothetical intentions.

## 2 Experimental Design

We conducted a mousetracking study (Experiment **M**) and an eye-tracking study (Experiment **E**), which shared a common structure.

Participants were recruited from the subject pool at Caltech and were screened, so that they participated only once in this study. Twenty-eight male subjects participated in Experiment **M** and 17 participated in Experiment **E**. [2] [3]

[1] There is only one study directly comparing results from both measures on a common task (Lohse and Johnson, 1996).

[2] Only male subjects were recruited, because it is desirable to have a set of consumer goods for which preferences of the subjects are not too different.

[3] Two additional subjects participated in Experiment **M**, but their data were excluded from the analysis (online appendix A.3).

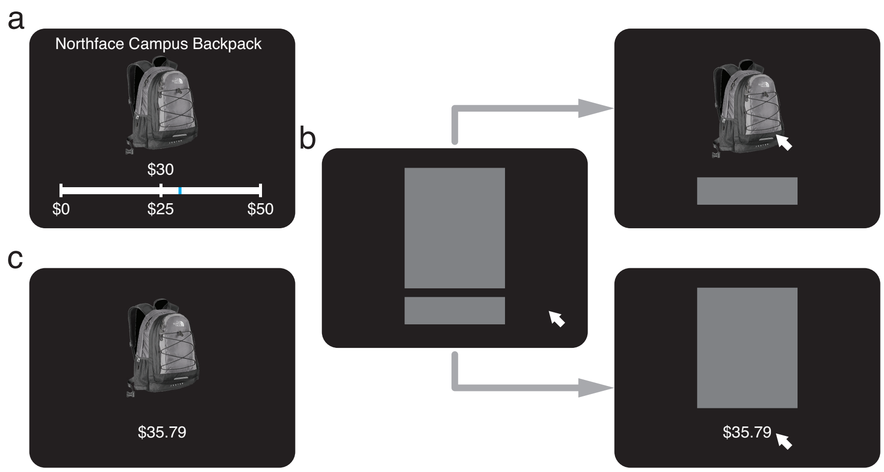


FIGURE 1: Example screens. (a) WTP reporting trials. (b) Purchasing trials in Experiment **M**. (c) Purchasing trials in Experiment **E**.

**Procedure.** The experiment consisted of four blocks: a willingness-to-pay (WTP) reporting block, a hypothetical purchase block, a real purchase block, and a "surprise" real purchase block. Mousetracking and eye-tracking were used only in the three purchase blocks. Subjects were told that they would earn up to $50 for completing the experiment. Detailed instructions for each part were given immediately prior to that part (online appendix G). Therefore, participants were unaware of the existence of two real purchase blocks, while they were in the hypothetical purchase block. We did not counter-balance the order of the hypothetical and real blocks intentionally (see discussion in online appendix A.4).

In the WTP reporting block, subjects were shown images of 120 consumer products (Table S7), one at a time and in random order. They were asked to state a maximum hypothetical WTP for each item, between $0 and $50, using a slider (Fig. 1a). Upon completion of the first part, products were ranked in descending order of the reported WTPs, except for those with WTP of $50. The 60 products from the top were selected for each subject and distributed to the hypothetical and real blocks. In this manner, we prepared two disjoint subject-specific sets of 30 products with matched WTP distributions while excluding extremely low-WTP (and potentially low-familiarity) products. Each of the 60 products was presented to the subject three times, with a different offer price each time. Three prices were determined based on the product's WTP (see online appendix A.1).

In the hypothetical purchase block, subjects were shown a product image with an offer price and asked to make a hypothetical purchase decision by responding with a Yes or No key press. In the real purchase block, subjects were informed that one of the trials would be randomly chosen at the end of the experiment, and whatever decision they had made in the chosen trial would be implemented.

In the "surprise" real purchase block, the same 90 ($30 \times 3$) product-price pairs that had been presented in the earlier hypothetical trials were shown again. This surprise real part was designed to measure switches from hypothetical to real decisions for the same set of items presented once in each condition. Note that the offer prices for each product remained identical to those in the hypothetical block.

At the end of the experiment, one trial from the real or surprise real block was randomly selected. If the subject had made a purchase decision at the offered price in the selected trial, he paid the price out of his \$50 endowment, received any remainder in cash at the end of the experiment, and the product was shipped to him. If the decision in the selected trial was to not buy, the subject received the full \$50 in cash and did not receive any product.

It is important to note that WTP was elicited solely to prepare two sets of items with similar values. We do not use WTP in the analysis, even though it is closely related to purchase decisions, for practical reasons— subject-specific measures of WTP are more difficult to collect than visual attention.

**Visual attention.** We recorded how long participants spent viewing the product image and the offer price in the purchasing blocks.

In Experiment **M**, subjects saw two gray opaque boxes on the screen behind which a product image and the offered price were hidden (Fig. 1b). Subjects had to click and hold the mouse button on one of the boxes to see the information behind it, and they were able to see either the product or the price at any given time. The viewing times of products and prices were recorded by tracking mouse events occurring on the boxes— that is, the time elapsed from the moment when the gray box opened to the moment when it closed and aggregated within a trial. In addition to viewing times, "latency" was defined as the time between the final box closing and when a choice was entered to capture last-minute contemplation to reach a decision. There was no time limit. Before the start of the hypothetical purchase block, subjects went through five practice rounds to familiarize themselves with the interface.

In Experiment **E**, opaque boxes were removed and subjects freely viewed information on the screen at the pace they desired (Fig. 1c). Gaze data were collected from subjects using the head-mounted eye-tracking system (see online appendix A.2).

# 3 Results

**Choice and visual attention.** Some summary statistics are presented in Table 1. Since the distributions of the WTPs were approximately matched between hypothetical and real blocks by construction, if there was no hypothetical bias, subjects should have chosen to buy goods at the same rate in the two blocks. The hypothetical purchase rates were 56.0% and 55.9% in the two experiments while the real purchase rates were 25.6% and 16.7%, producing a significant reduction in purchase rates in both experiments (two-sided $t$-test, $p < 0.001$). We also observe frequent decision switches (Table S2): more than half (55.5% and 69.4% in Experiments **M** and **E**, respectively) of hypothetical Yes were switched to No in the surprise real block, compared to a very low rate of switching in the opposite direction (5.2% and 3.6%). [4] Overall, subjects exhibited a significant hypothetical bias.

Table 1 shows that subjects on average fixated longer on the price and the image in the real block than in the hypothetical block before making a Yes decision, while that pattern was reversed before making a No decision (except for image viewing time in Experiment **M**). Similarly, subjects fixated longer on both product and price when they made real Yes decisions than real No decisions. In the hypothetical condition, however, the differences are not significant. [5] Results from

[4] By design, participants faced exactly the same product-price pairs in the hypothetical and surprise real blocks. In the absence of hypothetical bias, subjects should make the same decisions between these two blocks. Note that subjects responded to prices to some extent even in the hypothetical block (see online appendix B.1).

[5] We also examine "spatial gaze distribution maps" using gaze data from Experiment **E**, and obtain qualitatively

Table 1: Summary statistics.

| | Experiment **M** | | | | | Experiment **E** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Average | Hypothetical | | Real | | $p$-value | Hypothetical | | Real | | $p$-value |
| Purchase percentage | 55.99 | (2.36) | 25.59 | (3.90) | < 0.01 | 55.88 | (3.39) | 16.67 | (1.98) | < 0.01 |
| WTP ($) | 23.51 | (1.11) | 23.51 | (1.11) | 1.00 | 26.91 | (1.18) | 26.86 | (1.17) | 0.34 |
| Price ($) | 21.06 | (0.98) | 21.10 | (0.98) | 0.30 | 24.13 | (1.05) | 24.07 | (1.04) | 0.36 |
| Response time (sec) | 4.01 | (0.17) | 4.43 | (0.36) | 0.12 | 2.30 | (0.22) | 2.16 | (0.19) | 0.11 |
| Image viewing time (sec) | 0.95 | (0.08) | 1.50 | (0.21) | < 0.01 | 1.32 | (0.14) | 1.33 | (0.12) | 0.85 |
| by decision: Yes | 0.95 | (0.08) | 3.60 | (0.84) | < 0.01 | 1.43 | (0.25) | 2.68 | (0.42) | < 0.01 |
| by decision: No | 0.97 | (0.10) | 1.22 | (0.14) | 0.05 | 1.33 | (0.11) | 1.16 | (0.10) | 0.01 |
| Price viewing time (sec) | 0.70 | (0.06) | 0.64 | (0.07) | 0.03 | 0.49 | (0.05) | 0.43 | (0.05) | 0.07 |
| by decision: Yes | 0.71 | (0.07) | 1.09 | (0.16) | < 0.01 | 0.51 | (0.07) | 0.70 | (0.10) | < 0.01 |
| by decision: No | 0.71 | (0.06) | 0.58 | (0.06) | < 0.01 | 0.49 | (0.05) | 0.39 | (0.04) | 0.01 |
| Pre-choice latency (sec) | 0.75 | (0.06) | 0.67 | (0.09) | 0.09 | – | – | – | – | – |
| by decision: Yes | 0.74 | (0.06) | 1.08 | (0.19) | 0.04 | – | – | – | – | – |
| by decision: No | 0.82 | (0.08) | 0.62 | (0.07) | 0.32 | – | – | – | – | – |

Standard errors of means are presented in parentheses. $p$-values are from two-sided $t$-tests comparing hypothetical and real blocks. Pre-choice latency was measured only in Experiment **M**.

logistic regressions of purchase decisions (presented in online appendix Table S4) confirm these observations: longer viewing times for price and image were significant predictors of purchase decision only in the real condition, even after controlling for the price of the item.

There is a notable difference in latency, which is the duration between the last time subjects viewed the price or the image, and the time at which they made a decision (precisely defined only in Experiment **M**). This pre-choice latency was significantly longer for real Yes compared to

similar results (online appendix B.3).

real No decisions (two-sided $t$-test, $p < 0.01$), but there was no such difference in hypothetical decisions. This extra pre-choice latency plausibly reflects additional last-minute contemplation before choosing to actually buy the product (Fig. S6).

Furthermore, pre-choice latencies in the hypothetical condition were longer when subjects later made a No decision rather than a Yes decision in the surprise real condition (Yes: $0.64$ s; No: $0.84$ s; two-sided $t$-test $p < 0.001$; Fig. S6). That is, subjects who took a longer time post-viewing before making a hypothetical choice were more likely to change their minds and say No when asked to choose for real. This is the first clue that features of hypothetical decisions might have some predictive power for whether hypothetical choices translate into the same real choices, for the same products.

**Predicting choices.** The main goal of this study is to investigate whether we could predict consumers' actual purchase decisions using the information on visual attention. To answer this question, we performed a linear discriminant analysis (LDA) of purchase decisions. As predictor variables, we used price, price viewing time, image viewing time, pre-choice latency (in Experiment **M**) as well as "other viewing time" (i.e., the duration of the gaze at blank screen areas which show neither image nor price; in Experiment **E**), and response time (RT). [6] We compare three models: "price only", "price and viewing times", and "price and RT". For each model, we repeated a cross-validated LDA to obtain a prediction success rate for each subject (see online appendix B.4 for detail). We measured the performance of each model by the prediction accuracy averaged across subjects.

Fig. 2 shows that viewing times do indeed improve prediction accuracy, to a modest extent. Adding viewing times to price in predicting real purchase decisions improved accuracy from 62.7 to 69.1%, and from 62.0 to 68.5%, in Experiments **M** and **E**, respectively. On the other hand, prediction of hypothetical choices was not improved by adding viewing times (66.2% and 65.3% in Experiment **M**; 62.2% and 62.9% in Experiment **E**).

[6] There was no clear-cut way to measure latency as defined above in Experiment **E** unless subjects actually closed their eyes after the last fixation until the decision submission. Hence, we used the total duration of the gaze at blank areas instead.

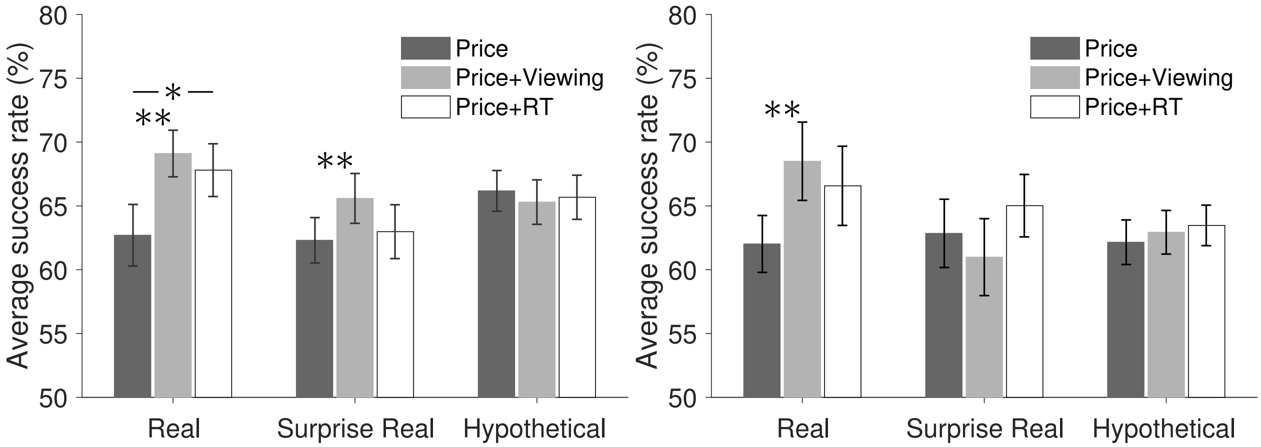


FIGURE 2: Average success rates for classification of decisions by condition in Experiment **M** (left) and Experiment **E** (right). Error bars indicate standard errors. $**$ : $p < 0.01$, $*$ : $p < 0.05$, one-sided $t$-test.

A much more challenging test, which is central to our question, is whether viewing times collected in *hypothetical* trials can improve prediction of decisions *for the same products* in the surprise real trials. We find that the average success rate was significantly improved from 62.3 to 65.6% by incorporating viewing times in Experiment **M** (one-sided $t$-test, $p < 0.01$), but no significant improvement is observed in Experiment **E** (62.8 to 61.0%). Another prediction exercise in which viewing times are replaced with RT does not provide significant improvement in prediction (62.3 to 63.0%). These results suggest that pre-choice measures of visual attention can be informative predictors of real choices and can potentially work as a practical tool for correcting hypothetical bias, but only with mousetracking data.

It is possible that some participants' choices can be classified rather accurately and others cannot. Given the heterogeneity in visual fixation patterns, we might also expect that different subsets of predictors could improve prediction for different subjects. The average success rates presented in Fig. 2 mask individual heterogeneity, but there is a room for improving prediction accuracy. Indeed, by searching for *the best combination* of predictors for each individual subject, we can improve the average success rate (for prediction of surprise real choices using hypothetical viewing times) to 68.3% in Experiment **M** and 66.8% in Experiment **E** (see online appendix B.4 and Figs. S12, S13). Importantly, the best combination of predictors includes at least one type of viewing time for more than 80% of subjects.

**Informational content in visual attention.** One may wonder why viewing times recorded in the hypothetical trials could improve prediction of choices in corresponding surprise real trials, even though those same viewing times did not add much in predicting choices in the hypothetical block.

In Experiment **M**, fixations on both image and price were longer in hypothetical Yes decisions that later resulted in "switches" to No (Table S3). In these switch trials, participants also had longer pre-choice latencies (0.86 s in switch trials, 0.62 s in stick trials; Fig. S6). Logistic regressions confirm that not only price but also price viewing time and latency were significant predictors of later decision switches (from hypothetical Yes to surprise real No) in Experiment **M** (Table 2).

It is likely that the predictive power came from this information, which we could obtain only in Experiment **M**. One explanation is that subjects spent longer before making decisions, since they were unsure (or indifferent) between buying and not buying, as suggested by the drift-diffusion model (Konovalov and Krajbich, 2017; Krajbich et al., 2010; Krajbich and Rangel, 2011). In hypothetical trials resulting in a Yes that later is switched, participants collected more information (= longer fixations) are still not really sure that they want to buy (= longer latency), but responded with a reluctant Yes decision anyway. Since subjects were forced to make a choice in our experiments, they might use non-consequential Yes decision as a tiebreaker in a difficult hypothetical question. The longer fixations and pre-choice latency could thus be indicators of hesitation, despite choosing Yes.

TABLE 2: Marginal effects from random-effects logistic regression of decision switch (switch = 1, stick = 0; conditional on hypothetical Yes).

| | Experiment **M** | | | Experiment **E** | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Price | 0.006 *** | | 0.006 *** | 0.010 *** | | 0.010 *** |
| | (0.002) | | (0.002) | (0.003) | | (0.003) |
| Image viewing | 0.000 | 0.002 | | 0.031 | 0.041 | |
| | (0.014) | (0.015) | | (0.024) | (0.028) | |
| Price viewing | 0.038 *** | 0.040 *** | | 0.010 | 0.014 | |
| | (0.010) | (0.010) | | (0.017) | (0.017) | |
| Latency/other | 0.055 *** | 0.055 *** | 0.057 *** | 0.007 | 0.005 | 0.008 |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.014) | (0.015) |
| # Observations | 1,411 | 1,411 | 1,411 | 842 | 842 | 842 |

Independent variables are measured during the hypothetical block. $*** : p < 0.001$, $** : p < 0.01$, $* : p < 0.05$. Viewing times (image, price, latency/other) are standardized within subject, across conditions.

# 4 Discussion

We explored whether visual attention that is easy to measure— attention to product images and prices— is associated with the tendency to overstate hypothetical purchase intentions, compared to real purchases.

A natural hypothesis that states "individuals who are looking at image (price) longer would (would not) buy" does not seem to hold in our data. In general, price viewing time is shorter than image viewing time, probably because a simple number is processed more quickly than a more complex product image. However, we observed differences in viewing times when they answered Yes and when they answered No in the real block. Such differences were not present in the hypothetical block.

We further investigated to what extent visual attention helps to predict purchasing decisions. We found that adding viewing times to prices in cross-validated linear discriminant analysis of purchases improves accuracy from 62.3 to 65.6% for surprise real purchases using viewing times in corresponding hypothetical block, but only when viewing times are recorded by mousetracking. Even though these improvements are not large in magnitude, they are significant. Even small improvements of forecast accuracy of this scale can be enormously important for firms forecasting consumer behavior in highly competitive markets.

Mousetracking and eye-tracking have been used widely in cognitive psychology and experimental economics to uncover cognitive processes behind many domains of decision making, including consumer choice under time pressure (Reutskaja et al., 2011), information acquisition in complex multi-attribute multi-alternative environment (Gabaix et al., 2006), bargaining (Camerer et al., 1993; Johnson et al., 2002), and strategic thinking (Brocas et al., 2014; Costa-Gomes et al., 2001; Knoepfle et al., 2009; Wang et al., 2010). However, little is known about the relative advantages of these two methods, since most of the existing studies (except for Lohse and Johnson, 1996) used either one of the methods.

Our results suggest that mousetracking seems to be more sensitive than eye-tracking, in two ways. First, choices in surprise real trials were better predicted with hypothetical viewing times in the mousetracking sessions than in the eye-tracking sessions (Fig. 2). Second, the differences in viewing times between hypothetical and real choices were larger when measured by mousetracking compared to eye-tracking. Motor movement of a mouse is more effortful and deliberative than fast eye saccades. As a result, there will be fewer random, low-information mouse movements compared to eye saccades. If so, mouse movements are actually clearer evidence of underlying deliberate decision processes than eye movements are.

As noted in the introduction, the two leading methods for predicting real choice from hypothetical reports are statistical adjustment, and using instructions to respondents that are intended to produce more realistic reported choices. Our method is a different kind of statistical adjustment, using pre-choice cognitive data that can be easy to measure. Furthermore, unlike special instructions to respondents, which require substantial internal validity and may not work well for all subjects and choices, measuring visual attention is relatively effortless and does not require special comprehension or internalization by subjects. Given the small, but promising incremental predictive power of viewing times in predicting real choice, a more finely-tuned version of our method using viewing times could prove to be useful on larger scales.

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