Valuing Reminders in Attention Management

Junjie Ren*

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Abstract

Do people value their attention optimally? Existing findings suggest that individuals systematically undervalue by how much attention-improving technologies, in particular reminders, can boost their chance of completing future tasks. In a theory-driven experiment, we revisit this question and elicit a measure of individuals' valuation of reminders that is free from arbitrary risk preference, under an incentive scheme of accumulating probability points to win a binary lottery. We find that individuals are still revealed to not fully appreciate the effectiveness of reminders, even after ruling out risk preference. The violation of optimality cannot be explained by potential probability weighting.

Keywords: Rational inattention, reminder, risk aversion, probabilistic incentive, willingness to accept, probability equivalent, probability weighting

*Department of Economics, National University of Singapore, `junjie.ren@outlook.com`.

1 Introduction

Evidence from economics and psychology has documented that attention is scarce and costly[1]. With limited cognitive resources, people become inattentive easily and keep forgetting to complete tasks. Various attention-improving technologies have been invented to help people manage attention efficiently: Material devices such as sticky notes, kitchen timers, and reminder letters, and software such as reminders in the form of text messages, emails, smartphone notifications, etc. However, daily experience suggests that with the market of reminders, we still constantly fail to complete tasks that we have planned ahead. We even ignore the reminders that we have set up beforehand and choose not to attend to the scheduled task.[2] A natural question is: Do people correctly perceive the value of those attention-improving technologies? We try to answer this question using evidence from an online, theory-driven survey experiment, examining the effectiveness of reminders in the context of task completion and people's valuation of reminders. We find that people are systematically undervaluing reminders and underestimating the effectiveness of reminders, and the results can not be explained by risk preference and probability weighting. Our experiment provides evidence violating the prediction of rational inattention theories that people can correctly perceive the limitation in their attention and value attention-improving technologies optimally.

We follow Bronchetti et al. (2023) who use revealed-preference approaches to derive restrictions on what rational management of limited attention implies. Results from their field and laboratory experiments suggest that there is a departure from the full optimality benchmark: Individuals undervalue and underuse attention-increasing technologies, i.e., the effectiveness of reminders is systematically underestimated. Specifically, in their survey-completion experiment, reminders are effective in increasing the completion rate of the incentivized survey scheduled in the future, with effect size of up to 40 percentage points in various task delays. Individuals' valuation of the reminders should be responsive to the task incentive: The higher the reward, the higher the value of reminders, as the chance of completion is higher with reminders. If the incentive increases by \$1, under optimality, the valuation of reminders should increase accordingly by $40\% \times \$1 = \$0.4$. However, individuals' response is significantly lower, with less than \$0.1 increase per additional \$1 incentive.

This paper speaks directly to the findings from their survey completion experiment. We point out that risk aversion could lead to the undervaluation of reminders that Bronchetti et al. (2023) observe. We rule out any confounding effect of arbitrary risk preferences by changing the entire payout scheme of the experiment into a binary lottery,

[1]See Loewenstein and Wojtowicz (2023) for a review.

[2]An extreme example of inattention is the surprisingly low medication adherence of patients with HIV, which is a fatal disease but controllable with proper medication. Only 62% of HIV patients achieved optimal adherence rate (of >90%) according to Ortego et al. (2011).

where individuals earn probability points to win a fixed prize. Under expected utility, individuals' utility increases linearly in probability, independently of any risk preference stemming from the shape of utility functions. We find that reminders raise the task completion rate by approximately 34 percentage points. Our model predicts that individuals' valuation of reminders should respond to incentives, and the response should be equal to this effect size: With an expected increase of $1 in incentive, individuals' average valuation increases by $0.34. However, our participants appear to be far less responsive than predicted. When the expected incentive increases $1, individuals' valuation only increases by 18 cents, which is equivalent to an 18 percentage points increase in the task completion rate. Further, we investigate what might drive this deviation. We find that probability weighting, a key component of prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Wu and Gonzalez, 1996; Prelec, 1998), still fail to explain the deviation from the optimality prediction. Finally, we explore potential drivers of the task completion behavior among one's personality traits. We find that conscientiousness plays a non-trivial role in increasing task completion rate across incentive schemes and levels, but the violation of optimality still holds after taking into account of personality traits.

One concern of the existing finding is that their conclusion crucially relies on their assumption of utility quasilinear in financial incentives. They attempt to address the potential confounding issue of risk aversion. However, their arguments are reasonably challenged. First, they calibrate their empirical results by assuming individuals are risk averse with constant absolute risk aversion (CARA) or constant relative risk aversion (CRRA) coefficients drawn on estimates from prior studies.[3] An important observation of their calibrated result is that, under CARA coefficient $\alpha = 0.2$ by Holt and Laury (2002), the calibrated incentive effect on valuation is the closest to their empirical estimates. Second, they measure the level of risk aversion for the subset of participants who finished the survey, and test whether the deviation from optimality is alleviated after controlling for risk aversion. They find no effect of risk aversion on the deviation. However, this does not take into account the fact that the level of risk aversion of the participants who did not finish the task might be systematically different from the finishers.

This paper contributes to several strands of the literature. First, our work relates to the growing literature of rational inattention since the seminal work of Sims (2003) that has been influential in modelling behaviors while treating attention as a limited resource (Gabaix, 2014, 2019).[4] Rational inattention models assume that individuals perceive their limitation in attention correctly and manage it optimally. Substantial effort has been devoted to testing the assumptions and predictions of rational inattention models. Evidence from both lab and field include Gabaix et al. (2006); Hanna et al. (2014); Bartoš et al. (2016); Martin (2016); Carvalho and Silverman (2019); Caplin et al. (2020);

[3]See Appendix E of Bronchetti et al. (2023).

[4]See also Caplin (2016), Gabaix (2019), and Maćkowiak et al. (2023) for reviews.

Ambuehl et al. (2022); Dean and Neligh (2023).

Second, this paper provides evidence on the discrepancy between perceived and actual value of reminders, or more generally, nudges. Our experimental setting focusing on the effects of reminders contribute to the literature on policy interventions inspired by rational inattention designed to help individuals conserve attention when performing tasks, ranging from reminders to stick to savings plans (Karlan et al., 2016) to technologies providing feedback on one's resource use (Tiefenbeck et al., 2018; Brülisauer et al., 2020).

Methodologically, this paper relates to the literature on binarized scoring rule (BSR, Hossain and Okui, 2013), or more generally, lottery tickets (probability points) to win a prize, as an incentive scheme. Danz et al. (2022) argues that BSR can elicit center-biased (i.e., less extreme) beliefs. Moreover, our measurement of individual valuation by Willingness To Accept (WTA) is related to the literature on the disparity between WTA and WTP. A recent study by Chapman et al. (2023) documents evidence of endowment effect that WTA is higher than WTP for the same risky prospect, but they find little evidence that the endowment effect is related to loss aversion, contrary to popular theories.

The remaining part of this paper proceeds as follows. In Section 2 we first show how risk aversion could lead to the undervaluation of reminders, and then we present a simplified model of costly attention of Bronchetti et al. (2023) that is free from risk preference. Section 3 introduces our experimental design. Section 4 shows our empirical results and Section 5 concludes.

2 Theoretical framework

In this section, we start the theoretical discussion by extending and generalizing Bronchetti et al. (2023)'s model to show that alternative functional forms could explain the departure from the theoretical prediction of optimal attention allocation. Then, we address the confounding issue of functional form by replacing monetary incentive with probabilistic incentive.

2.1 Valuing reminders under monetary incentive

Consider a situation where individuals are required to complete a task that is scheduled in the future. An individual i's problem is to choose a level of costly attention $a_i^j \in [0,1]$ to maximize

$$U_i^j(a_i^j \mid w, r) = f(r+w)a_i^j + f(w)(1-a_i^j) - k_i^j(a_i^j; \boldsymbol{\theta}),$$

where $j = 1$ if i will receive a set of reminders about completing the task and 0 otherwise. r denotes the monetary incentive for task completion and w denotes a monetary offer for i to give up the reminders. When $w = 0$, the offer is rejected and $j = 1$; when $w > 0$, the offer is accepted and $j = 0$. $f(\cdot)$ is the utility function of money, with $f(0) = 0$

and $f'(\cdot) > 0$. Here we do not impose any assumption on the curvature of $f(\cdot)$, i.e., the sign of $f''(\cdot)$ is undetermined, to allow for any form of risk preference. The attention level a_i^j corresponds to the probability of completing the future task given reminder assignment j and incentive r, namely $a_i^j = \Pr(z_i = 1 \mid j, r)$, where $z_i = 1$ indicates task completion for i and $z_i = 0$ otherwise.[5] $k_i^j(a_i^j; \boldsymbol{\theta})$ is the attention cost function with parameters $\boldsymbol{\theta}$. We assume convexity of the cost function $k_i^j(a_i^j)$ for all a_i^j: $k_i^{j\prime}(a_i^j) > 0$ and $k_i^{j\prime\prime}(a_i^j) > 0$. The optimal attention level a_i^{j*} can be solved from the first order condition $f(r+w) - f(w) = k_i^{j\prime}(a_i^{j*})$.

Individual i evaluates the set of reminders by trading off the reminders against an offer for her to give them up. By accepting the offer, she sells the reminders (such that $j = 0$) and will receive the offer of value w together with task incentive r (if any) after the task completion is realized. The maximum utility is given by

$$V_i^0(w, r) \equiv f(r+w)a_i^{0*} + f(w)(1 - a_i^{0*}) - k_i^0(a_i^{0*}).$$

Rejecting the offer will keep the reminders ($j = 1$), getting $w = 0$ and yielding the maximum utility

$$V_i^1(r) \equiv f(r)a_i^{1*} - k_i^1(a_i^{1*}).$$

When $w = 0$, $V_i^0(r) = f(r)a_i^{0*} - k_i^0(a_i^{0*}) < V_i^1(r)$. Since V_i^0 is increasing in w, there exists some W such that for all $w \geqslant W$, we have $V_i^0(w, r) \geqslant V_i^1(r)$. In other words, there exists a minimum offer W that makes forgoing the reminders (and receiving the offer) at least as attractive as keeping the reminders but forgoing the offer. We define the minimum offer W as the willingness to accept (WTA) of the reminders, the minimum amount of money that the individual is willing to accept to forgo the reminders. W equates the maximum utility when the offer is rejected and $j = 1$ (getting reminders) and the maximum utility when the offer is accepted and $j = 0$ (no reminders), i.e., $V_i^0(W, r) = V_i^1(r)$. Then we have

Before we present our main prediction that relates to the valuation of reminders, measured by WTA, to the actual effect of reminders, i.e., the improvement in task completion due to reminders, it is convenient to first define the difference in task completion rate with reminders ($j = 1$) and without them ($j = 0$) as

$$D_i(z_i = 1 \mid r) := \Pr(z_i = 1 \mid j = 1, r) - \Pr(z_i = 1 \mid j = 0, r).$$

We take the expectations of $W_i(r)$ and $D_i(r)$ across individuals at the population level to obtain $W(r) \equiv \mathbb{E}_i[W_i(r)]$ and $D(z = 1 \mid r) \equiv \mathbb{E}_i[D_i(z_i = 1 \mid r)]$. For an average individual, applying Envelope Theorem to $W(r)$ implies the following theorem (see

[5]The probability of task completion is further determined by the probability of being attentive the task (q_a) and the probability of taking (auxiliary) actions to complete the task (q_o).

Appendix A.1 for proofs).[6]

Theorem 1 *For the monetary valuation of reminders $W(r)$, it holds that*

(i) If the utility function $f(\cdot)$ exhibits risk neutrality, then

$$\frac{\mathrm{d}}{\mathrm{d}r}W(r) = D(z = 1 \mid r). \tag{1}$$

(ii) If the utility function $f(\cdot)$ exhibits risk aversion, then

$$\frac{\mathrm{d}W}{\mathrm{d}r} = \frac{A}{D}a_i^{1^*} - \frac{1}{D}a_i^{0^*}, \tag{2}$$

where

$$A = \frac{f'(r)}{f'(r+W)}$$

and

$$D = a_i^{0^*} + \frac{f'(W)}{f'(r+W)}(1 - a_i^{0^*})$$

There exists $W^* \in (0, r)$ such that for all $W < W^*$,

$$\frac{\mathrm{d}}{\mathrm{d}r}W(r) < D(z = 1 \mid r).$$

Equation (1) of Theorem 1 replicates the main result of Bronchetti et al. (2023) and states that, under risk neutrality, when task incentive r increases, the valuation of reminders $W(r)$ will respond to the increase in incentive according to the reminders' effect on task completion. Figure 1 illustrates the intuition behind Equation (1). The shaded area represents the increase in valuation of reminders when incentive r increases by Δr. Bronchetti et al. (2023) normalize the marginal utility of incentive to one (thus assuming risk neutrality) and predict that the LHS statistic should be equal to the RHS statistic. Their finding from a survey completion experiment is that LHS < RHS, indicating that individuals undervalue reminders ("bandwidth enhancements") compared to the effective attention improvement.

However, when $f(\cdot)$ exhibits risk aversion, the equality of incentive effect on WTA and reminders' effect, $D(z = 1 \mid r)$, does not always hold. Part (ii) of Theorem (1) characterizes the condition under which the incentive effect is smaller than reminders' effect, which could explain the divergence between the two empirical statistics on either side of Equation (1). For any WTA that is below the cutoff W^*, incentive effect is smaller than reminders' effect.

[6]Here we focus on the case where $W(r)$ is differentiable and present the derivative version theorem. For an integral version without the assumption of differentiability, see Bronchetti et al. (2023).

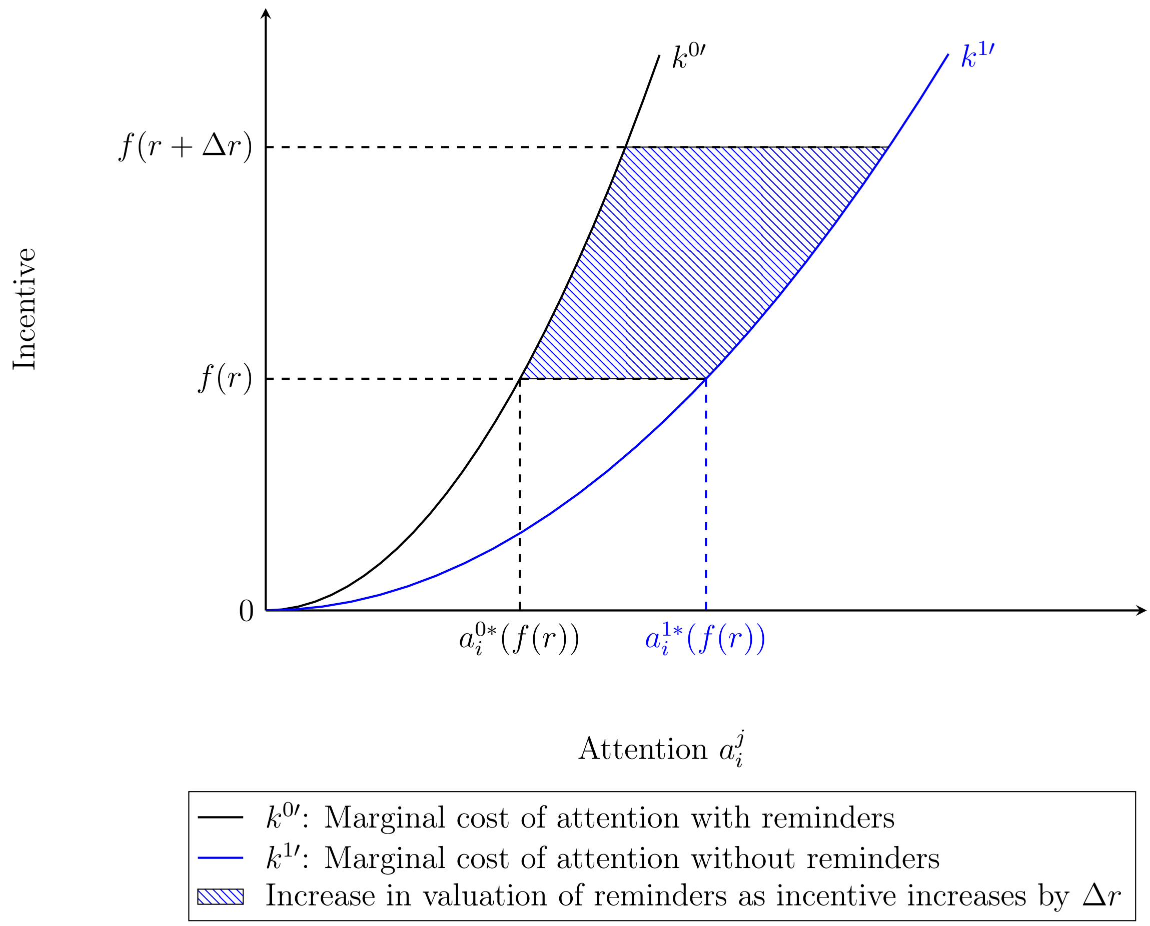


Figure 1: Illustration of Theorem 1 under risk neutrality, with $f'(\cdot)$ normalized to 1

2.2 Valuing reminders under probabilistic incentive

To address the confounding issue of potential responsiveness to monetary incentive, we change the entire payout scheme into a binary lottery. Instead of money, participants gain probability points to win a fixed prize. Formally, an individual i's utility function under probabilistic incentive is given by

$$U_i^j(a_i^j \mid r) = rf(X)a_i^j - k_i^j(a_i^j;\boldsymbol{\theta}),$$

where $a_i^j \in [0,1]$ is the level of costly attention under reminder configuration $j \in \{0,1\}$. Constant X is the fixed prize of a lottery, $f(X)$ is the utility of receiving \$$X$. By an abuse of notation, we denote the probability of winning \$$X$ by $r \in (0,1)$, which is the effective task incentive. $k_i^j(a_i^j;\boldsymbol{\theta})$ is a convex attention cost function with parameters θ. The optimal attention level a_i^{j*} can be solved from the first order condition $rf(X) = k_i^{j\prime}(a_i^{j*};\boldsymbol{\theta})$.

The utility function is identical to the one in Section 2.1 except that incentive r is transformed from money into probability. The purpose of the shift in incentive scheme is to make individuals think of probability as "currency", as probability points determine with which probability they win a final prize. Under expected utility theory, individuals' utility increases linearly in probability, independently of any risk preference stemming from the shape of the utility function.[7]

To evaluate a set of reminders about completing the task, individual i now trades off the reminders against an offer in the form of a simple lottery (with varying winning probability) for her to give them up. Her valuation is then measured by the lowest probability that she is willing to accept to win the lottery, in exchange for the reminders, which we call the *probability equivalent* (PE) to the WTA for reminders. Suppose that winning the prize \$$X$ with probability p_i^j achieves the maximum utility under reminder assignment j:

$$p_i^j f(X) = \max_{a_i^j} U_i^j(a_i^j \mid r).$$

Then, PE for reminders is defined as the (scaled) difference between the maximum utility when $j = 1$ (getting reminders) and that when $j = 0$ (no reminders):

$$P_i(r) := p_i^1 - p_i^0 = \frac{1}{f(X)}\left(\max_{a_i^1} U_i^1(a_i^1 \mid r) - \max_{a_i^0} U_i^0(a_i^0 \mid r)\right).$$

Take the expectation of $P_i(r)$ at the population level to obtain $P(r) \equiv \mathbb{E}_i[P_i(r)]$. For an average individual, following the intuition of Envelope Theorem, we have the following theorem (proof is provided in Appendix A.2).

Theorem 2 *Average probabilistic valuation of reminders PE satisfies*

$$\frac{\mathrm{d}}{\mathrm{d}r}P(r) = D(z = 1 \mid r). \tag{3}$$

Theorem 2 shows that the incentive effect on PE is equal to the increase in task completion rate due to reminders. Compared to the monetary version Theorem 1, adopting probabilistic incentive removes the confounding factor marginal utility of monetary incentive, so Equation (3) exactly illustrates how changes in PE relate to the observed changes in task completion rate, as a function of probabilistic incentive r. Equation (3), together with its monetary version counterpart Equation (1), is the key "non-parametric" testable restriction in our experiment.

3 Experimental design

Following Bronchetti et al. (2023), we design a two-part task-completion experiment to estimate the effect of reminders on task completion rate and to elicit participants' valuation of the reminders, in terms of willingness to accept (WTA) or probability equivalent

[7] As individuals are exposed to more probabilistic reasoning, we will also discuss the possibility of probability weighting, which is an important implication of cumulative prospect theory, in Section 4.4.

(PE). Part 1 of the experiment is a survey that takes approximately 10 minutes immediately after one consents to participate the experiment. Participants will get a fixed reward $1 if they finish Part-1 survey. Part 2 is a second survey with additional incentives. It also takes approximately 10 minutes, but is only available in three weeks from the day of Part 1, with a one-week window for completion.

Participants are randomized to receive, or not receive, a set of three reminder emails during the one-week window of Part 2 to remind them of completing the survey, therefore the treatment effect of reminders on the completion rate of Part 2 can be estimated. In Part-1 survey, we elicit participants' valuations of the set of reminders in response to varying forms and levels of incentive. The incentive of Part 2 is in the form of either a pecuniary payment or a binary lottery. To be more specific, half of the participants are randomized to earn a monetary bonus if they complete Part-2 survey, and a participant's incentive is either $2, $3, $4, or $5, each of which is randomly selected with equal probability. In contrast, the remaining half of the participants have a chance to win a $10 prize if they complete Part 2, with winning probability of either 20%, 30%, 40%, or 50%, each of which is equally likely to be selected. Therefore, we vary the incentive level in the same fashion for both forms of incentive: either $2, $3, $4, or $5 in *expectation*. Accordingly, in Part 1 participants' valuation of reminders is measured by either their willingness to accept (WTA) to give up the reminders, in terms of monetary bonus, or the probability equivalent (PE) to willingness to accept.

3.1 Implementation

Participants were recruited from Amazon Mechanical Turk between July 6 and July 18, 2022. Worker requirements were set so that participants should have completed between 100 and 10,000 approved tasks and have a task approval rate of 99% or above. The recruitment was restricted to workers from the United States. On each day the recruitment started at 9AM and ended at 1:30AM of the next day (US Eastern Time) to take account of workers from all time zones of the US.

Upon starting the experiment, participants were informed of the two-part structure of the experiment, the incentives for completing each part, and the reminders that may be assigned to them. Participants were told that Part 1 is a 10-minute survey, and they could earn $1 if they complete it. They were told that Part 2 is a second 10-minute survey that is only available three weeks from Part 1, and they would have one week to complete it. Half of the participants were randomly assigned to WTA condition, where the Part-2 incentive was randomly selected from $2, $3, $4, and $5, while the other half of the participants were assigned to PE condition, where the Part-2 incentive was randomly selected from 20, 30, 40, and 50 lottery tickets to win a $10 prize. Participants were informed that their bonus for completing Part-2 survey would be randomly selected from the aforementioned incentive levels. Further, participants were informed that they might receive a set of three reminder emails through the MTurk platform to remind them of completing Part-2 survey, and the reminders would be sent at 9AM (US Eastern Time) on the first, middle, and last day of the one-week completion window. Participants were explicitly told that it is not certain that they will receive these reminders, and it would be either the case that the computer lets them choose whether they receive the reminders, or the case that the computer determines whether they receive them. In other words, there is a chance that participants' choice about the reminders would be implemented, and they would not receive any reminders unless they are selected to receive them.

In order to begin Part-1 survey, participants were required to correctly answer two understanding questions, one about the incentive structure and the other about reminders.[8] After that, each participant was shown four questions eliciting valuation of reminders in succession, in which four possible incentive levels showed up in a random order. In each question, participants were asked to report, using a slider, the minimum offer that they were willing to accept to give up the set of reminders, in response to a certain incentive level.[9] Participants in WTA condition were asked to report at least how much money (up to \$4) they were willing to accept to give up the reminders, while participants in PE condition were asked to report at least how many lottery tickets (up to 40) they were willing to accept to give up reminders. With the variation in incentive levels, we can estimate the incentive effect on WTA and PE, i.e., the left-hand side of Equations 1 and 3. To consider possible preference for no reminder, i.e., the case where nuisance cost of reminders is sufficiently high, we extended the range of the slider to the negative domain. We allowed participants to report negative WTA (PE) up to $-\$1$ (-10 lottery tickets).

We exogenously assigned the treatment of reminders to estimate reminders' effects on the completion rate of Part-2 survey, i.e., the right-hand side of Equations 1 and 3. 45% of the participants were randomized to receive reminders and 45% not to receive any reminders. We selected the remaining 10% of the participants into an "endogenous group", to implement their choices in Part 1 in the following way. For each participant, given his or her randomly selected incentive level for Part-2 survey completion, the minimum acceptable offer that this participant indicated (in response to this incentive) will be compared to a random offer of the computer, which is a randomly selected value from the range of the slider. If the computer's offer is better or equal to the minimum offer acceptable, the offer will be accepted and this participant will not receive any reminders;

[8]Specifically, participants need to select all correct answers for two multiple choice questions. The first question is about the incentive structure, with the following correct answers: "I will earn \$1 for sure if I complete Part-1 survey" and "I will earn either \$2, \$3, \$4, or \$5 (20, 30, 40, or 50 lottery tickets to win the \$10 prize) if I complete Part-2 survey". The second question is about the reminders, with the following correct answers: "It is not certain that I will receive reminder emails", "I may receive reminders because of my choices", and "I may receive reminders because the computer selected me at random".

[9]See Figures B1 and B2 in Appendices for screenshots of the interface of valuation elicitation.

otherwise the offer will be rejected and the set of reminders will be sent in due course.

4 Results

4.1 Sample description

In total 838 participants completed Part-1 survey. One restriction that we impose on the sample is that we exclude the participants who reported the highest possible valuation when the incentive level is the lowest ($2 or 20 lottery tickets), termed "top-coded", as well as those who reported the lowest possible valuation when the incentive level is the highest ($5 or 50 lottery tickets), termed "bottom-coded", in which cases their valuation will never increase as incentive increases. Such patterns can attenuate the incentive effect on valuation toward zero, resulting in an exaggerated divergence from the actual treatment effect of reminders on task completion.[10] This restriction leaves us a sample of 662 participants, 374 of which were assigned to the monetary incentive group and 288 the probabilistic incentive group. which is the sample we analyze in this section. Estimation results for reminder valuation are presented in Section 4.2.

Among the 662 participants, 10% of the sample (64) was assigned to the "endogenous group": Their respective reminder treatment condition, i.e., whether or not getting reminders during the completion window of Part 2, was determined based on their choices in Part 1, as explained in Section 3.1. The remaining 598 participants were randomly assigned reminders so that the treatment effect of reminders on task completion can be estimated. Table 1 reports the size and relative proportion (within column) of each treatment group by incentive scheme, incentive level, and reminder treatment. Within each incentive scheme, group sizes are well balanced across incentive levels and reminder treatments. The exogenous assignment of reminders enables us to estimate the treatment effect of reminders on task completion, and we report the results in Section 4.3.

4.1.1 Discussion

We observe a higher dropout rate in the probabilistic incentive group relative to monetary incentive group, resulting in a smaller sample size of the probabilistic incentive group (257 versus 341). Table C9 of the Appendix reports sample size changes in the screening process of Part 1. Provided that our recruitment was programmed to be balanced across treatment conditions throughout the recruiting process, this imbalance could be due to several reasons pertaining to the "lottery design" per se. For example, probabilistic incentive scheme is apparently more complicated than paying money and could lead to more time spent understanding the rule. Figure C4 compares the time spent on instrucitons

[10] In spite of potential attenuation bias in the estimate of incentive effect on valuation, we report the results using the uncensored full sample in Appendix D for reference.

Table 1: Group size by incentive scheme, incentive level, and reminder treatment

	Monetary incentive			Probabilistic incentive		
E[Incentive]	Reminder	No reminder	Total	Reminder	No reminder	Total
2	34	42	76	37	38	75
	(19.65)	(25.00)	(22.29)	(28.03)	(30.40)	(29.18)
3	50	42	92	25	25	50
	(28.90)	(25.00)	(26.98)	(18.94)	(20.00)	(19.46)
4	45	42	87	34	38	72
	(26.01)	(25.00)	(25.51)	(25.76)	(30.40)	(28.02)
5	44	42	86	36	24	60
	(25.43)	(25.00)	(25.22)	(27.27)	(19.20)	(23.35)
Total	173	168	341	132	125	257
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)

Note: This table presents the size of each treatment group by incentive scheme, incentive level, and reminder treatment. The sample used in this table excludes top-coded and bottom-coded participants. Percentages in parentheses indicate the relative frequency of each group within column (reminder or no reminder treatment).

and comprehension test by participants who completed Part 1 survey under the two incentive schemes, while Figure C5 compares the same feature but focuses on participants who failed to pass the comprehension test. Both figures suggest that participants spent more time reading the instructions about probabilistic incentive and trying to pass the comprehension test, no matter whether they eventually passed or failed the test. However, Table C10 shows that the probabilistic incentive scheme does not seem to lead to more failed trials in the comprehension test among those who completed Part-1 survey. Moreover, a major source of the imbalance comes from the number of participants who timed out in comprehension test, as shown in Table C9. Comparing the timed-out participants in both schemes in Table C11, more time-outs in probabilistic incentive group is not driven by multiple failed trials, which could be a source of potential frustration, but rather immediate exit without even trying (zero failed trials is equivalen to zero trials since they eventually timed out), which may suggest that paying in the form of a lottery is less attractive than money.

4.2 Incentive effect on reminder valuation

As each participant answered four elicitation questions about their valuation of reminders in response to varying incentive levels (under a certain incentive scheme), we are able to estimate the responsiveness of reminder valuations to changes in incentive level with a hybrid of within- and between-subject design. We first compare WTA and PE Table 2 presents summary statistics of WTA and PE at each incentive level. We rescale probabilistic incentives and PE to their expected value for ease of comparison. Both mean WTA and mean PE increase monotonically as incentive increases incrementally. The last column reports the p-value of the test for equality of mean WTA and mean PE at each incentive level, and we find that mean WTA and mean PE are never significantly different at any incentive level.

Figure C3 further shows how valuations respond to incentive changes by depicting cumulative distributions of WTA and PE by incentive level. We note that a proportion of the elicited valuations are clustered at the top choice \$4 when the incentive level is high. If participants have even higher valuations over \$4 but their choices are capped by the upper bound of the response range, this would lead to underestimated valuations, especially at higher incentive levels \$4 or \$5, and thus attenuate the estimated incentive effect as well, at least at higher incentive levels.

Table 2: Summary statistics of WTA and PE for reminders by incentive level

	WTA			PE			
E[Incentive]	Mean	SE	Obs.	Mean	SE	Obs.	p
2	1.6401	0.0563	374	1.6063	0.0709	288	0.7049
3	1.9356	0.0626	374	1.8677	0.0764	288	0.4885
4	2.1278	0.0712	374	2.0149	0.0841	288	0.3038
5	2.2872	0.0761	374	2.1486	0.0870	288	0.2311

Note: This table presents the summary statistics of WTA and PE for reminders by incentive level. Probabilistic incentive levels and PE are converted into expected values (e.g., 20% chance of winning \$10 is equivalent to \$2 in expectation). The last column shows the p-values of the test for the equality of mean WTA and mean PE at each incentive level.

We formally estimate the incentive effect on WTA and PE in Table 3. Columns (1) and (3) reports the estimates using all responses in Part 1. On average, when the monetary incentive increases by \$1, WTA increases by 21 cents (SE = 2.44 cents). For probabilistic incentive, when the winning probability of lottery increases by 10 percentage points, PE increases by 1.77 pp. (SE = 0.30 pp.), which in expectation is equivalent to 17.7 cents increase in valuation for every \$1 increase in task incentive.[11] Testing for the equality of the estimated incentive effect on WTA in column (1) and that on PE in column (3), we find no significant difference between them (Wald test $p = 0.2873$).

Further, one limitation of our experimental design is that the range of the valuation to report is capped at \$5, or equivalently 50% chance probabilistic incentive. This could potentially attenuate the incentive effect toward zero, as any valuation that is higher than \$4 is bounded by \$4. To examine potential attenuation, columns (2) and (4) exclude the valuations elicited in Part 1 in response to the top level of incentive \$5 (50%). The estimated incentive effect on WTA in column (2) is 0.2439 (SE = 0.0338), which is marginally significantly different from the estimate 0.2133 in column (1) using all responses (Wald

[11]Compared to the full-sample estimates in Table D13, the incentive effect is nearly doubled for the censored sample.

Table 3: Incentive effect on WTA and PE

	WTA		PE	
	(1)	(2)	(3)	(4)
Incentive	0.2133***	0.2439***	0.1774***	0.2043***
	(0.0244)	(0.0338)	(0.0304)	(0.0450)
Constant	1.2510***	1.1696***	1.2884***	1.2166***
	(0.0855)	(0.1015)	(0.1064)	(0.1351)
Observations	1,496	1,122	1,152	864
Participants	374	374	288	288
Adjusted R^2	0.737	0.736	0.689	0.676

Note: This table presents estimates of the effect of incentive on valuation of reminders. Column (2) excludes responses to the incentive level of \$5 and column (4) excludes responses to the incentive level of 50%. Participant fixed effects are controlled for in all columns. Cluster-adjusted (at participant level) standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

test $p = 0.0417$). For PE, excluding the top incentive level of 50% winning probability does not lead to a significant difference in the estimated incentive effects: Wald test p-value is 0.1854 for the equality of the coefficients in columns (3) and (4). Again, the incentive effect on WTA in column (2) is not significantly different from that on PE in column (4) (Wald test $p = 0.3897$).

As we employ a within-subject design in Part 1 of our experiment, in which participants are required to report their valuation for four different hypothetical incentive levels presented in a random order, participants' valuations might suffer form anchoring effect. That is, the incentive level that appears in the elicitation question shown in the first round and the response thereof might become an anchor, or a reference point, for the remaining questions, which may bias the estimated incentive effect. As the order of the incentive levels in the four rounds of elicitation questions is randomized, we are able to examine the concern for such an order effect. Tables 4 and 5 report the estimates of incentive effect using responses from subsets of rounds. In both tables, column (1) includes only the responses from the first round, which can be viewed as a completely between-subject experiment. Columns (2)–(4) add stepwise the responses to the question in the next round, so column (4) is identical to column (1) of Table 3. Column (5) uses responses in all four rounds as in column (4) but additionally controls for round fixed effects. As participants proceeded in the survey, the incentive effect on WTA slightly increases, as shown in Table 4, while in Table 5 the incentive effect on PE decreases, although the difference between the between-subject estimate in column (1) is not significantly different from the within-subject, all-round estimate in column (4). Controlling for the round fixed effects in column (5) barely changes the estimate.

Table 4: Incentive effect on WTA of reminders: Order effect

	WTA				
	(1) Round 1	(2) Rounds 1–2	(3) Rounds 1–3	(4) All rounds	(5) All rounds
Incentive	0.1592***	0.1413***	0.1864***	0.2133***	0.2122***
	(0.0599)	(0.0431)	(0.0298)	(0.0244)	(0.0242)
Constant	1.5823***	1.5635***	1.3729***	1.2510***	1.3956***
	(0.2136)	(0.1522)	(0.1044)	(0.0855)	(0.0934)
Round FE	No	No	No	No	Yes
Observations	374	748	1,122	1,496	1,496
Participants	374	374	374	374	374
Adjusted R^2	0.015	0.736	0.739	0.737	0.742

Note: This table presents estimates of the effect of incentive on WTA of reminders, examining order effects. Participants answered four rounds of elicitation questions about their reminder valuation, in which the incentive levels are shown in random order. Column (1) only includes responses in the first round, column (2) includes responses in the first and second rounds, column (3) includes responses in the first three rounds, and columns (4) and (5) include responses in all four rounds. Column (5) additionally controls for the round fixed effects. Participant fixed effects are controlled for in all columns. Cluster-adjusted (at participant level) standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Incentive effect on PE of reminders: Order effect

	PE				
	(1) Round 1	(2) Rounds 1–2	(3) Rounds 1–3	(4) All rounds	(5) All rounds
Incentive	0.2150***	0.1686***	0.1693***	0.1774***	0.1710***
	(0.0731)	(0.0501)	(0.0351)	(0.0304)	(0.0302)
Constant	1.3148***	1.4009***	1.3530***	1.2884***	1.4722***
	(0.2680)	(0.1809)	(0.1241)	(0.1064)	(0.1152)
Round FE	No	No	No	No	Yes
Observations	288	576	864	1,152	1,152
Participants	288	288	288	288	288
Adjusted R^2	0.025	0.747	0.728	0.689	0.695

Note: This table presents estimates of the effect of incentive on PE of reminders, examining order effects. Participants answered four rounds of elicitation questions about their reminder valuation, in which the incentive levels are shown in random order. Column (1) only includes responses in the first round, column (2) includes responses in the first and second rounds, column (3) includes responses in the first three rounds, and columns (4) and (5) include responses in all four rounds. Column (5) additionally controls for the order fixed effects. Participant fixed effects are controlled for in all columns. Cluster-adjusted (at participant level) standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Reminders' effect on completion rate and test of optimality

Figure 2 depicts the completion rates of Part 2 in monetary and probabilistic incentive conditions. In all incentive conditions (under both schemes and at all levels), reminders significantly increase the completion rate compared to the case without reminders. The treatment effect of reminders on completion rate is formally estimated in Table 6. Under the monetary incentive, reminders increase Part-2 completion rate by approximately 39 pp. (SE = 4.70 pp.). The reminders remain highly effective under probabilistic incentive, with an estimated treatment effect of approximately 34 pp. (SE = 5.78 pp.), which is slightly lower than but not significantly different from the effect size under monetary incentive (Wald test $p = 0.5495$). The baseline completion rate, indicated by the intercept, is 46 pp. without reminders under monetary incentive and 39 pp. under probabilistic incentive, meaning that more than a half of the participants failed to complete Part-2 survey, which is no better than a coin toss, yet reminders can substantially increase the probability to complete the task. The test for the equality of the estimated reminders' effect and the constant term fail to reject the null (Wald test $p = 0.5559$ and 0.7476, respectively), suggesting that the completion rate is doubled by the treatment of reminders, relative to the no reminder condition.

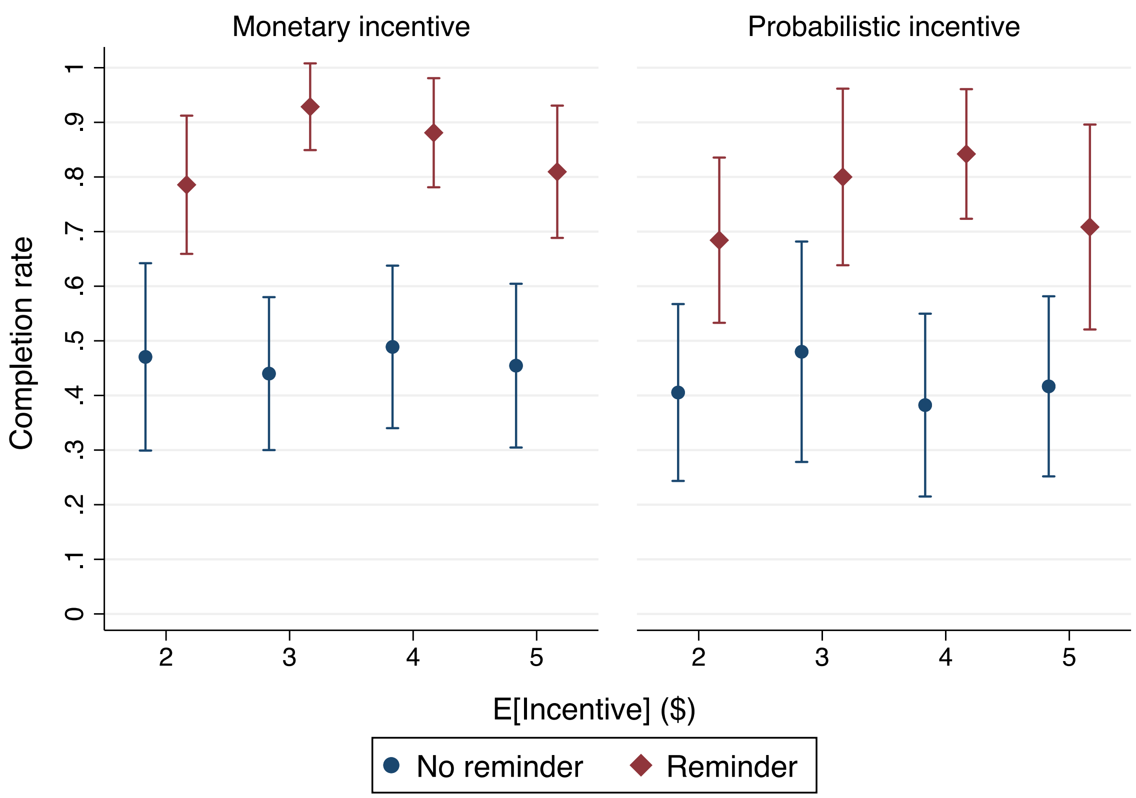


Figure 2: Part-2 completion rates in monetary and probabilistic incentive conditions

Table 6: Reminders' effect on Part-2 completion rate

	Completed Part 2	
	(1) Monetary	(2) Probabilistic
Reminder	0.3889***	0.3445***
	(0.0470)	(0.0578)
Incentive	0.0018	0.0083
	(0.0223)	(0.0262)
Constant	0.4561***	0.3873***
	(0.0883)	(0.1021)
Observations	341	257
Adjusted R^2	0.162	0.115

Note: This table presents estimates of the effect of reminders on the completion rate of Part-2 survey. Column (1) estimates the effect for participants in monetary incentive condition and column (2) in probabilistic incentive condition. Robust standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

After estimating the statistics on both sides of the equations (1) and (3) in Theorems 1 and 2, namely the left-hand side incentive effect on reminder valuation and the right-hand side reminder effect on completion, we are able to empirically test the optimality prediction of the model. We find that participants do not value reminders as highly as the effectiveness of reminders with respect to task completion: The incremental incentive effect on WTA is only 21 cents (SE = 2.44 cents), and that on PE is 17 pp. chance (SE = 3.04 pp.), which is equivalently 17 cents (SE = 3.04 cents) Both estimates of incentive effect are significantly different from their respective reminders' effect on task completion rate (Wald test $p < 0.01$ for both conditions), suggesting a departure from the optimality prediction in Theorems 1 and 2 assuming rational inattention.

4.4 Accounting for probability weighting

We have introduced the probability incentive scheme and the probability equivalent to WTA of reminders to address the issue that individuals could misperceive monetary incentive effect on WTA due to risk aversion. However, people may perceive probabilities in a distorted way, i.e., probability weighting in terms of overweighting small probabilities and underweighting high probabilities, as proposed by prospect theory and supported by experimental evidence (e.g., Bruhin et al. 2010). This may affect not only PE measure but also WTA measure, as long as probability is involved. In this section, we take into account probability weighting to capture the distortions in perceived probability and examine how the theoretical predictions are changed thereby.

4.4.1 Monetary incentive

An individual i's problem is to choose a level of costly attention a_i^j to maximize

$$U_i^j(a_i^j \mid w, r) = f(r+w)\pi(a_i^j) + f(w)[1-\pi(a_i^j)] - k_i^j(\pi(a_i^j); \boldsymbol{\theta}),$$

where $\pi(\cdot)$ is the probability weighting function. The incentive effect on WTA of reminders is obtained simply by replacing a_i^{j*} with $\pi(a_i^{j*})$ in Equation (2) in Theorem 1:

$$\frac{\mathrm{d}W}{\mathrm{d}r} = \frac{A}{D}\pi(a_i^{1^*}) - \frac{1}{D}\pi(a_i^{0^*}).$$

The incentive effect on WTA at the population level is

$$\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}r}\mathbb{E}_i[W_i(r)] &= \mathbb{E}_i\left[\frac{A}{D}\pi(a_i^{1*}) - \frac{1}{D}\pi(a_i^{0*})\right] \\
&= \mathbb{E}_i\left[\frac{\frac{A}{D}\pi(a_i^{1*}) - \frac{1}{D}\pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}} \cdot (a_i^{1*} - a_i^{0*})\right] \\
&= \mathbb{Cov}\left[\frac{\frac{A}{D}\pi(a_i^{1*}) - \frac{1}{D}\pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}}, (a_i^{1*} - a_i^{0*})\right] + \\
&\quad \mathbb{E}_i\left(\frac{\frac{A}{D}\pi(a_i^{1*}) - \frac{1}{D}\pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}}\right) \cdot \mathbb{E}_i[a_i^{1*} - a_i^{0*}].
\end{aligned}$$

On the right-hand side, $\mathrm{E}[a_i^{1*} - a_i^{0*}]$ is the difference in task completion rate due to reminder adoption. Therefore, we can test the prediction in reduced form to examine whether probability weighting plays a role.

4.4.2 Probabilistic incentive

An individual i's problem is to choose a level of costly attention a_i^j to maximize

$$U_i^j(a_i^j \mid r) = \pi(r)f(X)\pi(a_i^j) - k_i^j(\pi(a_i^j); \boldsymbol{\theta}),$$

where X is the final prize of Part-2 lottery, $f(X)$ is the utility of receiving \$$X$, and r is the probability of winning \$$X$, which is the effective task incentive.

The incentive effect on PE at the population level is

$$\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}r}\mathbb{E}_i[P_i] &= \pi'(r) \cdot \mathbb{E}_i[\pi(a_i^{1*}) - \pi(a_i^{0*})] \\
&= \pi'(r) \cdot \mathbb{E}_i\left[\frac{\pi(a_i^{1*}) - \pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}} \cdot (a_i^{1*} - a_i^{0*})\right] \\
&= \pi'(r) \cdot \Bigg(\mathrm{Cov}\left[\frac{\pi(a_i^{1*}) - \pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}}, (a_i^{1*} - a_i^{0*})\right] + \\
&\quad \mathbb{E}_i\left(\frac{\pi(a_i^{1*}) - \pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}}\right) \cdot \mathbb{E}_i[a_i^{1*} - a_i^{0*}]\Bigg).
\end{aligned}$$

We could again test this prediction in reduced form as in the WTA condition.

We further test whether probability weighting plays a role in Table 7. In columns (1) and (3), the dependent variable is the difference between the valuation of reminders (WTA or PE) and the increase in completion rate due to reminder adoption (ΔCompletion rate), while in columns (2) and (4), the dependent variable is the valuation of reminders and the increase in completion rate due to reminder adoption is moved to the right-hand side of the regression equation to be an independent variable. Results of both specifications suggest that probability weighting is not an issue that can explain the undervaluation of reminders.

Table 7: Testing for probability weighting

	WTA		PE	
	(1)	(2)	(3)	(4)
Incentive	0.1890***	0.1965***	0.1711***	0.1720***
	(0.0259)	(0.0255)	(0.0328)	(0.0327)
ΔCompletion rate		0.4640*		0.1417
		(0.2710)		(0.5579)
Constant	0.9385***	1.1203***	0.9755***	1.2587***
	(0.0905)	(0.1402)	(0.1149)	(0.2402)
Observations	1,364	1,364	1,028	1,028
Participants	341	341	257	257
Adjusted R^2	0.734	0.736	0.682	0.683

Note: This table presents regressions of testing for probability weighting. Columns (1) and (3)'s dependent variable is the difference between valuation (WTA or PE) and reminder effect. Columns (2) and (4) control for the reminder effect. Participant fixed effects are controlled for in all columns. Cluster-adjusted (at participant level) standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.5 Personality traits and task completion

What else might drive the substantial deviation from the optimality benchmark? We investigate this question from the task incompletion side of the equation. In Part 1, apart from asking participants to value reminders, we elicit their personality traits using the Short 15-item Big Five Inventory (BFI-S, Lang et al. 2011). We examine whether task completion behavior is driven by individual personality traits. Table 8 presents the estimated effects of each of the five factors in Big Five personality traits, namely, openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism[12], across different treatment conditions. We find that conscientiousness seems to play a non-trivial role in task completion, especially under monetary incentive scheme. Regardless of the

[12] These five factors may be remembered using acronyms "OCEAN" or "CANOE".

assignment of reminders, participants who are more conscientious have a higher completion rate. The positive effect of conscientiousness is perfectly sensible since it measures the sense that a person is being responsible, careful, or diligent and tend to be efficient and organized. As factors are measured on a 7-point Likert scale[13], the estimated effects suggest that with one unit increase in conscientiousness, the task completion rate will increase by approximately 8 pp. on average. The openness to experience is negatively related to the task completion, which is reasonable as participants with higher openness are less likely to be confined to the scheduled task that we arranged for them. In column (6), we examine reminders' effect on completion rate after controlling for personality traits. We find that the estimated coefficients are very close to the ones estimated in Table 6, meaning that although personality traits can drive the task completion behavior, the reminders are robustly effective for individuals of various personality.

Table 8: Part-2 completion rate and Big Five personality traits

	Completed Part 2					
	Monetary incentive			Probabilistic incentive		
	(1) Reminder	(2) No reminder	(3) Pooled	(4) Reminder	(5) No reminder	(6) Pooled
Openness	-0.0602^{**}	-0.0473	-0.0529^{**}	-0.0464	-0.0289	-0.0419
	(0.0270)	(0.0392)	(0.0227)	(0.0305)	(0.0443)	(0.0265)
Conscientiousness	0.0749^{***}	0.0863^{**}	0.0783^{***}	0.0899^{**}	0.0303	0.0565^{*}
	(0.0285)	(0.0387)	(0.0242)	(0.0431)	(0.0431)	(0.0299)
Extraversion	0.0060	-0.0304	-0.0137	-0.0561^{**}	-0.0506	-0.0524^{**}
	(0.0185)	(0.0271)	(0.0165)	(0.0279)	(0.0344)	(0.0219)
Agreeableness	-0.0047	0.0372	0.0199	-0.0145	-0.0177	-0.0146
	(0.0270)	(0.0341)	(0.0222)	(0.0381)	(0.0427)	(0.0291)
Neuroticism	-0.0168	-0.0172	-0.0157	0.0252	0.0017	0.0141
	(0.0181)	(0.0252)	(0.0158)	(0.0236)	(0.0292)	(0.0191)
Incentive	-0.0034	0.0013	0.0007	0.0249	-0.0020	0.0097
	(0.0274)	(0.0349)	(0.0218)	(0.0376)	(0.0375)	(0.0262)
Reminder			0.3712^{***}			0.3365^{***}
			(0.0475)			(0.0575)
Constant	0.8191^{***}	0.2159	0.3160	0.6004	0.6856^{*}	0.5079^{*}
	(0.2858)	(0.3643)	(0.2344)	(0.3633)	(0.4029)	(0.2777)
Observations	168	173	341	125	132	257
Adjusted R^2	0.047	0.015	0.196	0.049	-0.017	0.143

Note: This table presents estimates of the effect of Big Five personality traits on the completion rate of Part-2 survey. Columns (1)–(3) estimate the effect for participants in monetary incentive condition and columns (4)–(6) in probabilistic incentive condition. Columns (1) and (4) estimate the effect with reminders and columns (2) and (5) without reminders. Columns (3) and (6) pool the participants with and without reminders. Robust standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[13]The scale ranges from 1 to 7, where 1 means "does not describe me at all", and 7 means "describes me perfectly".

5 Conclusion

In this paper, we theoretically demonstrate the risk aversion problem that could explain the findings of undervaluation of attention-improving technologies, in particular reminders, by Bronchetti et al. (2023). We address this problem by employing a probabilistic incentive scheme of accumulating probability points to win a binary lottery, ruling out any form of risk preference stemming from the shape of utility functions. However, in our experiment, we still find that individuals systematically undervalue reminders under such incentive scheme: The empirical effects of reminders is raising the task completion rate by 34 percentage points, while individuals' valuation increases by only (equivalently) 18 cents with every $1 increase in expected task reward, which is equivalent to 18 percentage points increase in task completion rate. Our results are robust to order effects, distortion in perceived probability due to probability weighting, and personality traits.

The departure from the theory documented in this paper raises some open questions, such as what factors, whether external factors in the environment or intrinsic factors of the economic agent, can account for the departures, and whether people are misperceiving their attention costs, or the benefits of attention-increasing technologies. There is certainly a broader research agenda on whether and why attention is not correctly perceived and optimally managed.

References

Ambuehl, Sandro, Axel Ockenfels, and Colin Stewart, "Who opts in? composition effects and disappointment from participation payments," *Review of Economics and Statistics*, 2022, pp. 1–45.

Bartoš, Vojtěch, Michal Bauer, Julie Chytilová, and Filip Matějka, "Attention discrimination: Theory and field experiments with monitoring information acquisition," *American Economic Review*, 2016, *106* (6), 1437–75.

Bronchetti, Erin T, Judd B Kessler, Ellen B Magenheim, Dmitry Taubinsky, and Eric Zwick, "Is Attention Produced Optimally? Theory and Evidence From Experiments With Bandwidth Enhancements," *Econometrica*, 2023, *91* (2), 669–707.

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper, "Risk and rationality: Uncovering heterogeneity in probability distortion," *Econometrica*, 2010, *78* (4), 1375–1412.

Brülisauer, Marcel, Lorenz Goette, Zhengyi Jiang, Jan Schmitz, and Renate Schubert, "Appliance-specific feedback and social comparisons: Evidence from a field experiment on energy conservation," *Energy Policy*, 2020, *145*, 111742.

Caplin, Andrew, "Measuring and modeling attention," *Annual Review of Economics*, 2016, *8*, 379–403.

__ , Dániel Csaba, John Leahy, and Oded Nov, "Rational inattention, competitive supply, and psychometrics," *Quarterly Journal of Economics*, 2020, *135* (3), 1681–1724.

Carvalho, Leandro and Dan Silverman, "Complexity and sophistication," 2019. Working paper.

Chapman, Jonathan, Mark Dean, Pietro Ortoleva, Erik Snowberg, and Colin Camerer, "Willingness to accept, willingness to pay, and loss aversion," Technical Report, National Bureau of Economic Research 2023.

Danz, David, Lise Vesterlund, and Alistair J Wilson, "Belief elicitation and behavioral incentive compatibility," *American Economic Review*, 2022, *112* (9), 2851–2883.

Dean, Mark and Nathaniel Neligh, "Experimental tests of rational inattention," *Journal of Political Economy*, 2023, *131* (12), 3415–3461.

Gabaix, Xavier, "A sparsity-based model of bounded rationality," *Quarterly Journal of Economics*, 2014, *129* (4), 1661–1710.

__ , "Behavioral inattention," in "Handbook of Behavioral Economics: Applications and Foundations 1," Vol. 2, Elsevier, 2019, pp. 261–343.

__ , David Laibson, Guillermo Moloche, and Stephen Weinberg, "Costly information acquisition: Experimental analysis of a boundedly rational model," *American Economic Review*, 2006, *96* (4), 1043–1068.

Hanna, Rema, Sendhil Mullainathan, and Joshua Schwartzstein, "Learning through noticing: Theory and evidence from a field experiment," *Quarterly Journal of Economics*, 2014, *129* (3), 1311–1353.

Holt, Charles A and Susan K Laury, "Risk aversion and incentive effects," *American Economic Review*, 2002, *92* (5), 1644–1655.

Hossain, Tanjim and Ryo Okui, "The binarized scoring rule," *Review of Economic Studies*, 2013, *80* (3), 984–1001.

Kahneman, Daniel and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 1979, *47* (2), 263–292.

Karlan, Dean, Margaret McConnell, Sendhil Mullainathan, and Jonathan Zinman, "Getting to the top of mind: How reminders increase saving," *Management Science*, 2016, *62* (12), 3393–3411.

Lang, Frieder R, Dennis John, Oliver Lüdtke, Jürgen Schupp, and Gert G Wagner, "Short assessment of the Big Five: Robust across survey methods except telephone interviewing," *Behavior Research Methods*, 2011, *43*, 548–567.

Loewenstein, George and Zachary Wojtowicz, "The Economics of Attention," 2023. Mimeo.

Maćkowiak, Bartosz, Filip Matějka, and Mirko Wiederholt, "Rational inattention: A review," *Journal of Economic Literature*, 2023, *61* (1), 226–273.

Martin, Daniel, "Rational inattention in games: experimental evidence," 2016. Working paper.

Ortego, Carmen, Tania B Huedo-Medina, Javier Llorca, Lourdes Sevilla, Pilar Santos, Elías Rodríguez, Michelle R Warren, and Javier Vejo, "Adherence to highly active antiretroviral therapy (HAART): a meta-analysis," *AIDS and Behavior*, 2011, *15* (7), 1381–1396.

Prelec, Drazen, "The probability weighting function," *Econometrica*, 1998, pp. 497–527.

Sims, Christopher A, "Implications of rational inattention," *Journal of Monetary Economics*, 2003, *50* (3), 665–690.

Tiefenbeck, Verena, Lorenz Goette, Kathrin Degen, Vojkan Tasic, Elgar Fleisch, Rafael Lalive, and Thorsten Staake, "Overcoming salience bias: How real-time feedback fosters resource conservation," *Management Science*, 2018, *64* (3), 1458–1476.

Tversky, Amos and Daniel Kahneman, "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and Uncertainty*, 1992, *5*, 297–323.

Wu, George and Richard Gonzalez, "Curvature of the probability weighting function," *Management Science*, 1996, *42* (12), 1676–1690.

Appendix A Proofs

A.1 Proof of Theorem 1

WTA W is a value of w that solves the following equation:

$$f(r+w)a_i^{0*} + f(w)(1-a_i^{0*}) - k_i^0(a_i^{0*}) = f(r)a_i^{1*} - k_i^1(a_i^{1*}).$$

By implicit function theorem, the incentive effect on WTA is given by

$$\frac{\mathrm{d}W}{\mathrm{d}r} = \frac{f'(r)a_i^{1^*} - f'(r+W)a_i^{0^*}}{f'(r+W)a_i^{0^*} + f'(W)(1-a_i^{0^*})}.$$

Dividing through by $f'(r+W)$, the above equation can be rewritten as

$$\frac{\mathrm{d}W}{\mathrm{d}r} = \frac{Aa_i^{1^*} - a_i^{0^*}}{a_i^{0^*} + B(1-a_i^{0^*})},$$

where $A = A(W;r) = \frac{f'(r)}{f'(r+W)}$ and $B = B(W;r) = \frac{f'(W)}{f'(r+W)}$. Let D denote the denominator: $D = D(W;r) = a_i^{0^*} + B(1-a_i^{0^*})$. Then, the incentive effect on WTA becomes

$$\frac{\mathrm{d}W}{\mathrm{d}r} = \frac{A}{D}a_i^{1^*} - \frac{1}{D}a_i^{0^*} \equiv F(W;r).$$

(i) When the utility function $f(\cdot)$ exhibits risk neutrality, we immediately have $A = B = D = 1$. Then, $\mathrm{d}W/\mathrm{d}r = a_i^{1^*} - a_i^{0^*}$, which is the main result of Bronchetti et al. (2023).

(ii) When the utility function $f(\cdot)$ exhibits risk aversion, take the derivative of F with respect to W,

$$F'_W = \frac{1}{D^2}\left(\frac{\mathrm{d}}{\mathrm{d}W}\frac{A}{D}a_i^{1*} + D^{-2}D'_W a_i^{0*}\right).$$

Since

$$\frac{A}{D} = \frac{f'(r)}{f'(r+W)a_i^{0*} + (1-a_i^{0*})f'(W)},$$

it is straightforward to see that $\frac{\mathrm{d}}{\mathrm{d}W}\frac{A}{D} > 0$. Further, it can be shown that

$$D'_W = \frac{(1-a_i^{0*})}{f'^2(r+W)}[f''(W)f'(r+W) - f'(W)f''(r+W)] \geqslant 0,$$

where the equality holds for CARA utility functions and $D'_W > 0$ for CRRA utility functions. This is because, by definition, CARA implies that

$$\frac{f''(W)}{f'(W)} = \frac{f''(r+W)}{f'(r+W)},$$

while CRRA implies that

$$\frac{f''(W)}{f'(W)}W = \frac{f''(r+W)}{f'(r+W)}(r+W) \implies \frac{f''(W)}{f'(W)} = \frac{f''(r+W)}{f'(r+W)}\left(\frac{r}{W}+1\right) > \frac{f''(r+W)}{f'(r+W)}.$$

Therefore, we have $F'_W > 0$, $F(W)$ is increasing in W.

When $W = 0$, $A = f'(r)/f'(r) = 1$, so $F(0;r) = (a_i^{1*} - a_i^{0*})/D < a_i^{1*} - a_i^{0*}$, given that $D = a_i^{0*} + B(1 - a_i^{0*}) > 1$ because $B > 1$. When $W = r$, $A = B = f'(r)/f'(2r)$, so $D = a_i^{0*} + B(1 - a_i^{0*}) < B$ and also $D < A$. It can be shown that $F(r;r) > a_i^{1*} - a_i^{0*}$. To see this, we take the difference

$$F(W;r) - (a_i^{1*} - a_i^{0*}) = \frac{A-D}{D}a_i^{1^*} + \frac{D-1}{D}a_i^{0^*}.$$

Since $A > D > 1$ when $W = r$, the difference is positive and $F(r) > a_i^{1*} - a_i^{0*}$. By intermediate value theorem, there exists $W^* \in (0, r)$ such that $F(W^*) = a_i^{1*} - a_i^{0*}$. Because $F(W)$ is increasing in W, then for all $W \in (0, W^*)$, we have $F(W) < a_i^{1*} - a_i^{0*}$.

■

A.2 Proof of Theorem 2

By Envelope Theorem, taking the derivative of PE (in expectation) with respect to r, the probabilistic incentive, implies

$$\frac{\mathrm{d}}{\mathrm{d}r}P(r) = \mathbb{E}_i\left[\frac{\mathrm{d}}{\mathrm{d}r}p_i^1 - \frac{\mathrm{d}}{\mathrm{d}r}p_i^0\right] = \frac{1}{f(X)}\left(\mathbb{E}_i\left[\frac{\partial}{\partial r}U_i^1(a_i^{1*} \mid r)\right] - \mathbb{E}_i\left[\frac{\partial}{\partial r}U_i^0(a_i^{0*} \mid r)\right]\right),$$

where a_i^{j*} denotes the optimal attention level under configuration $j \in \{0, 1\}$. For either configuration j, we have

$$\frac{\partial}{\partial r}U_i^j(a_i^{j*} \mid r) = \frac{\partial}{\partial r}[rf(X)a_i^{j*} - k_i(a_i^{j*})] = f(X)a_i^{j*}.$$

Thus, the incentive effect on PE becomes

$$\frac{\mathrm{d}}{\mathrm{d}r}P(r) = a_i^{1*} - a_i^{0*} = \Pr(z = 1 \mid j = 1, r) - \Pr(z = 1 \mid j = 0, r) \equiv D(z = 1 \mid r).$$

■

A.3 Proof of probability weighting in WTA condition

FOC:

$$\frac{\mathrm{d}U_i^j}{\mathrm{d}a_i^j} = w'(a_i^j)\int_{-r}^{\infty}(b+r)\mathrm{d}G_i(b) - k_i^{j\prime}(a_i^j) = 0$$

$$\implies k_i^{j\prime}(a_i^j) = w'(a_i^j)\int_{-r}^{\infty}(b+r)\mathrm{d}G_i(b).$$

By Envelope Theorem, taking the derivative of WTA (in expectation) with respect to r, the task incentive, implies

$$\frac{\mathrm{d}\mathbb{E}_i[W_i(r)]}{\mathrm{d}r} = \mathbb{E}_i\left[\frac{\partial U_i^1(a_i^{1*} \mid r)}{\partial r}\right] - \mathbb{E}_i\left[\frac{\partial U_i^0(a_i^{0*} \mid r)}{\partial r}\right],$$

where a_i^{j*} denotes the optimal level of attention under configuration $j \in \{0,1\}$. Then, for either configuration j, we have

$$\begin{aligned}
\frac{\partial U_i^j(a_i^{1*} \mid r)}{\partial r} &= \frac{\partial}{\partial r}\left[\pi(a_i^{j*})\int_{-r}^{\infty}(b+r)\mathrm{d}G_i(b) - k_i(a_i^{j*})\right] \\
&= \pi(a_i^{j*}) \cdot \frac{\partial}{\partial r}\left[\int_{-r}^{\infty}(b+r)\mathrm{d}G_i(b)\right] \\
&= \pi(a_i^{j*}) \cdot \left[0 - \frac{\partial(-r)}{\partial r}(-r+r) + \int_{-r}^{\infty}\frac{\partial}{\partial r}(b+r)\mathrm{d}G_i(b)\right] \\
&= \pi(a_i^{j*}) \cdot .
\end{aligned}$$

Thus, the incentive effects on WTA becomes

$$\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}r}\mathbb{E}_i[W_i(r)] &= \mathbb{E}_i[\pi(a_i^{1*})\cdot] - \mathbb{E}_i[\pi(a_i^{0*})\cdot] \\
&= \mathbb{E}_i\left[\frac{\pi(a_i^{1*})}{a_i^{1*}} \cdot a_i^{1*}\right] - \mathbb{E}_i\left[\frac{\pi(a_i^{0*})}{a_i^{0*}} \cdot a_i^{0*}\right] \\
&= \left(\mathrm{Cov}\left[\frac{\pi(a_i^{1*})}{a_i^{1*}}, a_i^{1*}\right] + \mathrm{E}\left(\frac{\pi(a_i^{1*})}{a_i^{1*}}\right) \cdot \mathrm{E}[a_i^{1*}]\right) - \\
&\quad \left(\mathrm{Cov}\left[\frac{\pi(a_i^{0*})}{a_i^{0*}}, a_i^{0*}\right] + \mathrm{E}\left(\frac{\pi(a_i^{0*})}{a_i^{0*}}\right) \cdot \mathrm{E}[a_i^{0*}]\right); \\
\text{or } &= \mathbb{E}_i[(\pi(a_i^{1*}) - \pi(a_i^{0*}))\cdot] \\
&= \mathbb{E}_i\left[\frac{\pi(a_i^{1*}) - \pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}} \cdot (a_i^{1*} - a_i^{0*})\right] \\
&= \mathrm{Cov}\left[\frac{\pi(a_i^{1*}) - \pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}}, (a_i^{1*} - a_i^{0*})\right] + \\
&\quad \mathrm{E}\left(\frac{\pi(a_i^{1*}) - \pi(a_i^{0*})}{a_i^{1*} - a_i^{0*}}\right) \cdot \mathrm{E}[(a_i^{1*} - a_i^{0*})].
\end{aligned}$$

■

A.4 Proof of probability weighting in PE condition

FOC:

$$\frac{\mathrm{d}U_i^j}{\mathrm{d}a_i^j} = w'(a_i^j)\int_{-w(r)f(X)}^{\infty} [b + w(r)f(X)]\mathrm{d}G_i(b) - k_i^{j\prime}(a_i^j) = 0$$

$$\implies k_i^{j\prime}(a_i^j) = w'(a_i^j)\int_{-w(r)f(X)}^{\infty} [b + w(r)f(X)]\mathrm{d}G_i(b).$$

By Envelope Theorem, taking the derivative of PE (in expectation) with respect to r, the task incentive, implies

$$\frac{\mathrm{d}}{\mathrm{d}r}\mathbb{E}_i[P_i] = \mathbb{E}_i\left[\frac{\partial}{\partial r}\frac{U_i^1(a_i^{1*} \mid r)}{f(X)}\right] - \mathbb{E}_i\left[\frac{\partial}{\partial r}\frac{U_i^0(a_i^{0*} \mid r)}{f(X)}\right],$$

where a_i^{j*} denotes the optimal level of attention under configuration $j \in \{0,1\}$. Then, for either configuration j, we have

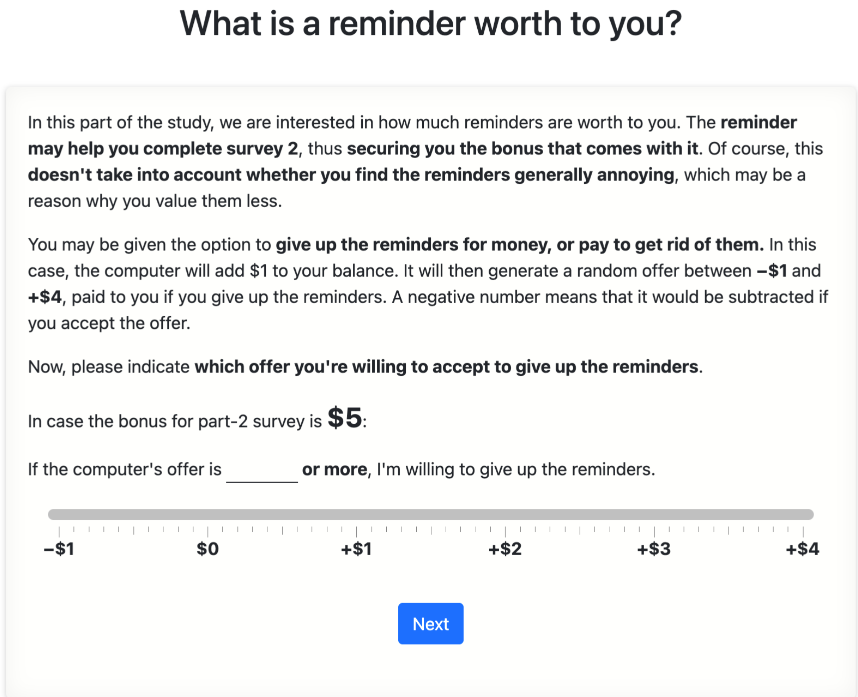
$$\begin{aligned}
\frac{\partial}{\partial r}\frac{U_i^j(a_i^{1*} \mid r)}{f(X)} &= \frac{\partial}{\partial r}\left[\pi(a_i^{j*})\int_{-w(r)f(X)}^{\infty}\left(\frac{b}{f(X)} + w(r)\right)\mathrm{d}G_i(b) - \frac{k_i(a_i^{j*})}{f(X)}\right] \\
&= \pi(a_i^{j*}) \cdot \frac{\partial}{\partial r}\left[\int_{-w(r)f(X)}^{\infty}\left(\frac{b}{f(X)} + w(r)\right)\mathrm{d}G_i(b)\right] \\
&= \pi(a_i^{j*}) \cdot \left[0 - \frac{\partial(-w(r)f(X))}{\partial r}\left(\frac{-w(r)f(X)}{f(X)} + w(r)\right)\right. \\
&\qquad\qquad \left. + \int_{-w(r)f(X)}^{\infty}\frac{\partial}{\partial r}\left(\frac{b}{f(X)} + w(r)\right)\mathrm{d}G_i(b)\right] \\
&= \pi(a_i^{j*}) \cdot w'(r).
\end{aligned}$$

Thus, the incentive effect on PE becomes

$$
\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}r}\mathbb{E}_i[P_i] &= \mathbb{E}_i\left[\pi(a_i^{1*})\cdot w'(r)\right] - \mathbb{E}_i\left[\pi(a_i^{0*})\cdot w'(r)\right] \\
&= w'(r)\cdot\left(\mathbb{E}_i\left[\frac{\pi(a_i^{1*})}{a_i^{1*}}\cdot a_i^{1*}(1-G_i(-w(r)f(X)))\right] - \mathbb{E}_i\left[\frac{\pi(a_i^{0*})}{a_i^{0*}}\cdot a_i^{0*}(1-G_i(-w(r)f(X)))\right]\right) \\
&= w'(r)\cdot\left(\mathrm{Cov}\left[\frac{\pi(a_i^{1*})}{a_i^{1*}}, a_i^{1*}(1-G_i(-w(r)f(X)))\right]+\right. \\
&\quad \mathbb{E}_i\left(\frac{\pi(a_i^{1*})}{a_i^{1*}}\right)\cdot\mathbb{E}_i[a_i^{1*}(1-G_i(-w(r)f(X)))] - \mathrm{Cov}\left[\frac{\pi(a_i^{0*})}{a_i^{0*}}, a_i^{0*}(1-G_i(-w(r)f(X)))\right]- \\
&\quad \left.\mathbb{E}_i\left(\frac{\pi(a_i^{0*})}{a_i^{0*}}\right)\cdot\mathbb{E}_i[a_i^{0*}(1-G_i(-w(r)f(X)))]\right); \\
\text{or } &= w'(r)\cdot\mathbb{E}_i\left[[\pi(a_i^{1*})-\pi(a_i^{0*})]\cdot\right] \\
&= w'(r)\cdot\mathbb{E}_i\left[\frac{\pi(a_i^{1*})-\pi(a_i^{0*})}{a_i^{1*}-a_i^{0*}}\cdot(a_i^{1*}-a_i^{0*})\right] \\
&= w'(r)\cdot\left(\mathrm{Cov}\left[\frac{\pi(a_i^{1*})-\pi(a_i^{0*})}{a_i^{1*}-a_i^{0*}}, (a_i^{1*}-a_i^{0*})\right]+\right. \\
&\quad \left.\mathbb{E}_i\left(\frac{\pi(a_i^{1*})-\pi(a_i^{0*})}{a_i^{1*}-a_i^{0*}}\right)\cdot\mathbb{E}_i[(a_i^{1*}-a_i^{0*})[1-G_i(-w(r)f(X))]]\right).
\end{aligned}
$$

■

Appendix B Experimental instructions and screenshots



What is a reminder worth to you?

In this part of the study, we are interested in how much reminders are worth to you. The **reminder may help you complete survey 2**, thus **securing you the bonus that comes with it**. Of course, this **doesn't take into account whether you find the reminders generally annoying**, which may be a reason why you value them less.

You may be given the option to **give up the reminders for money, or pay to get rid of them.** In this case, the computer will add $1 to your balance. It will then generate a random offer between **–$1** and **+$4**, paid to you if you give up the reminders. A negative number means that it would be subtracted if you accept the offer.

Now, please indicate **which offer you're willing to accept to give up the reminders**.

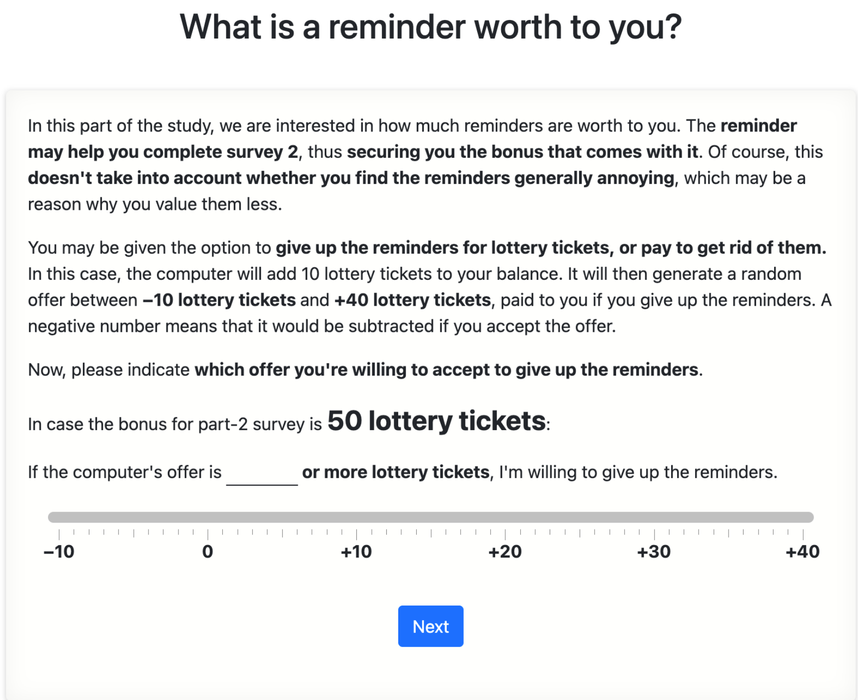
In case the bonus for part-2 survey is **$5**:

If the computer's offer is ______ **or more**, I'm willing to give up the reminders.

–$1 $0 +$1 +$2 +$3 +$4

Next

Figure B1: Screenshot of question eliciting willingness-to-accept



What is a reminder worth to you?

In this part of the study, we are interested in how much reminders are worth to you. The **reminder may help you complete survey 2**, thus **securing you the bonus that comes with it**. Of course, this **doesn't take into account whether you find the reminders generally annoying**, which may be a reason why you value them less.

You may be given the option to **give up the reminders for lottery tickets, or pay to get rid of them.** In this case, the computer will add 10 lottery tickets to your balance. It will then generate a random offer between **–10 lottery tickets** and **+40 lottery tickets**, paid to you if you give up the reminders. A negative number means that it would be subtracted if you accept the offer.

Now, please indicate **which offer you're willing to accept to give up the reminders**.

In case the bonus for part-2 survey is **50 lottery tickets**:

If the computer's offer is ______ **or more lottery tickets**, I'm willing to give up the reminders.

–10 0 +10 +20 +30 +40

Next

Figure B2: Screenshot of question eliciting probability equivalent

Appendix C Additional tables and figures

Table C9: Sample screening in Part 1 by incentive scheme

Stage	Monetary	Prob.	Total
Consented to participate	866	850	1,716
Failed attention check	12	6	18
Failed comprehension test	275	281	556
Timed out in instructions and comprehension test	107	178	285
Entered Part 1 survey	472	385	857
Timed out in survey	7	8	15
Failed to submit completion code	3	1	4
Completed Part 1 survey	462	376	838
Top-coded	82	78	160
Bottom-coded	6	10	16
Remaining	374	288	662

Table C10: Number of failed trials for participants who completed Part 1 under different incentive schemes

#Trials	Monetary	Prob.	Total
0	150	126	276
	(32.40)	(33.51)	(32.90)
1	182	157	339
	(39.31)	(41.76)	(40.41)
2	131	93	224
	(28.29)	(24.73)	(26.70)
Total	463	376	839
	(100.00)	(100.00)	(100.00)

Table C11: Number of failed trials of participants who timed out in instructions and comprehension test

#Trials	Monetary	Prob.	Total
0	23	50	73
	(21.50)	(28.09)	(25.61)
1	25	40	65
	(23.36)	(22.47)	(22.81)
2	59	88	147
	(55.14)	(49.44)	(51.58)
Total	107	178	285
	(100.00)	(100.00)	(100.00)

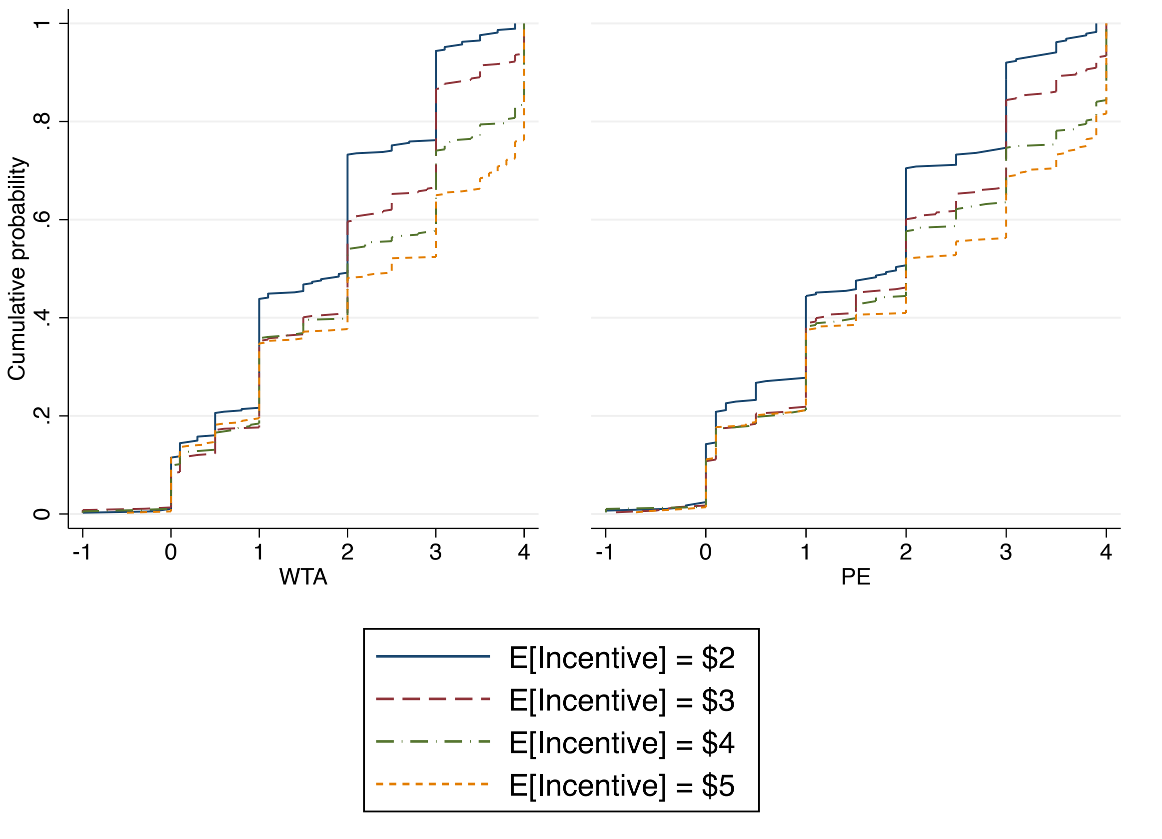


Figure C3: Cumulative distributions of willingness to accept vs. probability equivalent

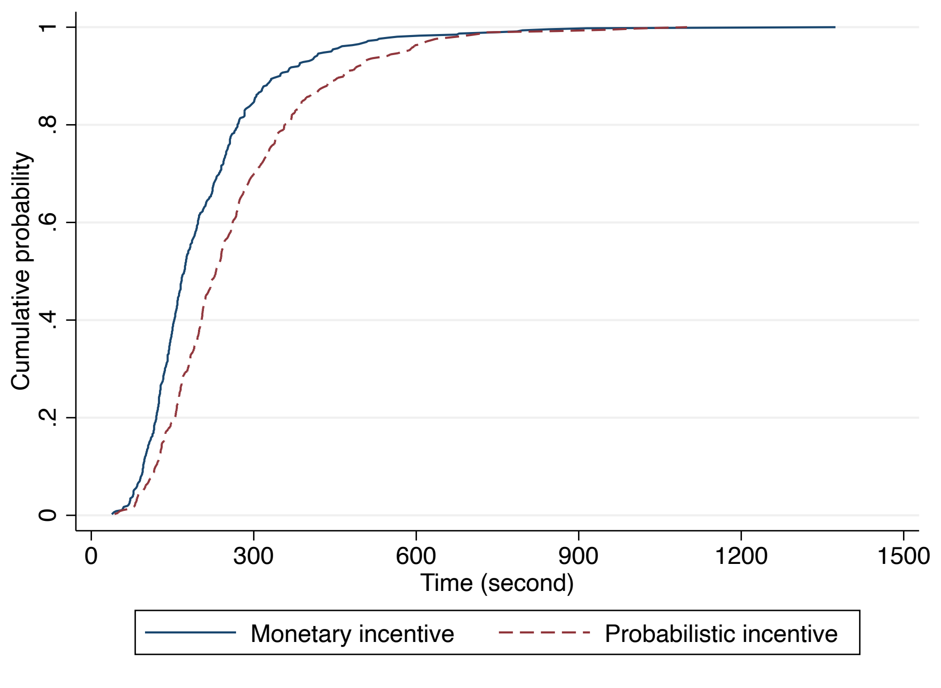


Figure C4: Cumulative distributions of time spent on instructions and comprehension test for participants who completed Part-1 survey: Monetary vs. probabilistic incentive ($p < 0.0001$)

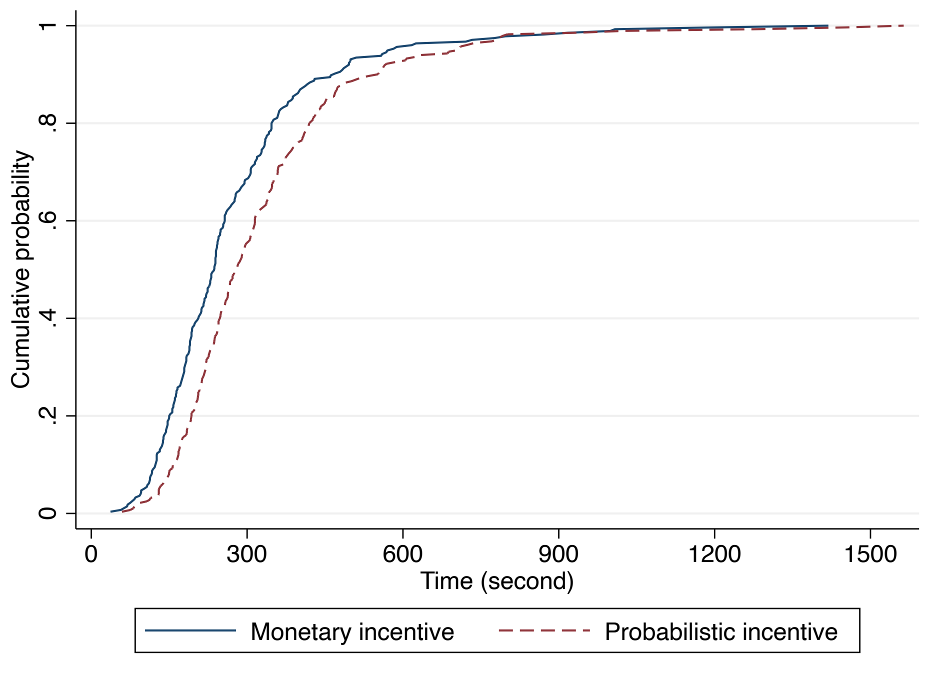


Figure C5: Cumulative distributions of time spent on instructions and comprehension test for participants who failed the comprehension test: Monetary vs. probabilistic incentive ($p < 0.001$)

Appendix D Results of the uncensored full sample

Table D12: Group size by incentive scheme, incentive level, and reminder treatment

	Monetary incentive			Probabilistic incentive		
E[Incentive]	Reminder	No reminder	Total	Reminder	No reminder	Total
2	42	50	92	44	50	94
	(19.81)	(23.92)	(21.85)	(26.83)	(28.90)	(27.89)
3	59	56	115	36	39	75
	(27.83)	(26.79)	(27.32)	(21.95)	(22.54)	(22.26)
4	57	49	106	40	47	87
	(26.89)	(23.44)	(25.18)	(24.39)	(27.17)	(25.82)
5	54	54	108	44	37	81
	(25.47)	(25.84)	(25.65)	(26.83)	(21.39)	(24.04)
Total	212	209	421	164	173	337
	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)	(100.00)

Note: This table presents the size of each treatment group by incentive scheme, incentive level, and reminder treatment. The sample used in this table is the full sample, including the top-coded and bottom-coded participants. Percentages in parentheses indicate the relative frequency of each group within column (reminder or no reminder treatment).

Table D13: Incentive effect on WTA and PE

	WTA		PE	
	(1)	(2)	(3)	(4)
Incentive	0.1288***	0.1544***	0.0984***	0.1251***
	(0.0240)	(0.0316)	(0.0264)	(0.0371)
Constant	1.8015***	1.7331***	1.8810***	1.8096***
	(0.0840)	(0.0948)	(0.0924)	(0.1113)
Observations	1,848	1,386	1,504	1,128
Participants	462	462	376	376
Adjusted R^2	0.731	0.766	0.764	0.785

Note: This table presents estimates of the effect of incentive on valuation of reminders. The sample used in this table is the full sample, including the top-coded and bottom-coded participants. Column (2) excludes responses to the incentive level of \$5 and column (4) excludes responses to the incentive level of 50%. Participant fixed effects are controlled for in all columns. Cluster-adjusted (at participant level) standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.