

Opportunity Cost Neglect in Preventive Health Decisions and Mitigating it by Talking Money

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Abstract

Standard health economic models require people to have full awareness the time opportunity costs of falling sick, such as missed work and leisure. Yet, people with bounded rationality may overlook them, showing the bias of opportunity cost neglect (OCN). We propose that this bias commonly exists in judgments about preventive health because opportunity costs are typically less salient and evaluable than direct costs. We show that this bias leads to various behavioral failures, such as insufficient prevention, insensitivity to time duration, and insensitivity to preventive measure efficacy. To mitigate this bias, we designed an intervention entitled “Active Unpacking with Money” (AUM), which directs DMs to actively calculate the monetary losses from experiencing a negative health condition over a specified time period. Through a series of seven consecutive online experiments, we demonstrate that: (1) AUM amplifies people’s perceived severity of health risks and their willingness-to-pay (WTP) for a guaranteed preventive measure; (2) AUM heightens people’s sensitivity to the length of a disease; and (3) AUM bolsters sensitivity to probabilistic information about prevention measure effectiveness. We discuss the practical significance of OCN and AUM as a potential nudging strategy.

JEL Codes: C91, D14, I10, I12

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“There seems to be plenty of “low-hanging fruit” available, from vaccines to bed nets, that could save lives at a minimal cost, but all too few people make use of such preventive technologies.” – Abhijit Banerjee and Esther Duflo, 2011, in “Poor Economics”

1. Introduction

In many situations, people fail to adopt simple preventive health measures, despite their proven benefits and cost-effectiveness (Dupas, 2009; Ashraf et al., 2010; Banerjee & Duflo, 2011). Such a phenomenon is sometimes referred to as “missing the low-hanging fruit for better health.” This “low-hanging fruit paradox” has significant implications in crucial areas such as poverty eradication (Banerjee & Duflo, 2011), health policy design (Goldie et al., 2006; Thaler & Sunstien, 2009), and global pandemic prevention (Bavel et al., 2020; Soofi et al., 2020). Understanding why individuals may neglect these actions is crucial for addressing larger economic and policy issues.

Among the many prevalent economic perspectives investigating this paradox, the behavioral lens has gained increasing popularity. Standard economic theory assumes that rational agents have perfect information and unlimited cognitive capacity. Thus, many “missed low-hanging fruits” are just an optimal behavior that is a consequence of weighing benefits and costs correctly (Grossmann, 1972; Bhattacharya et al., 1994). However, behavioral economists recognize the boundedness of rationality, indicating that people may deviate from perfectly rational behaviors in standard models due to various cognitive biases. Myopic judgments (Thaler & Benartzi, 2004; Kan, 2007; Wang & Sloan, 2018), health illiteracy and misinformation (Southwell et al., 2019; Krishna and Thompson, 2021), and biased risk perception (Brnstrm, 2010; Wolff et al., 2019; Arni et al., 2021) are all examples of decision biases that might lead to missed low-hanging fruits and compromise health and well-being. In our paper, we focus specifically on one bias, opportunity cost neglect (OCN), and link it to the “low-hanging fruit paradox.” With seven experiments, we document the prevalence of this bias, reveal its mechanisms, and propose targeted interventions.

Opportunity cost (OC) is a fundamental concept in economics, including the domain of health. Standard health demand models assume that time is a scarce resource, either allocated to productive activities that generates benefits³ or occupied by sickness, which yields no value. When individuals fall sick, the time lost due to illnesses thus represents an opportunity cost. Standard health economics (Grossmann, 1972; Bhattacharya et al., 1994) not only assume the existence of these costs, but also that people fully notice and consider them when making decisions. Nevertheless, opportunity cost neglect (of money and time) is frequently mentioned in behavioral economics and consumer behavior literature. People may concentrate on explicit and direct outcomes and neglect the implicit and indirect opportunity costs (Frederick et al., 2009; Spiller, 2011; Persson & Tinghög, 2020). Time-related OCN has also been recognized in recent literature (Chatterjee et al., 2016; Spiller, 2019), though there is some debate on its relative impact compared to money-related OCN. Importantly, time opportunity costs in health

³ The benefits can be income (work), health (exercise), or utility (leisure).

may have two features that increase the likelihood of neglect: (1) low *salience*, and (2) low *evaluability*.

Salience — the quality of a dimension, attribute, or piece of information being particularly noticeable or conspicuous — shapes consumer judgment and choices (Hoffman & Singh, 1997; Itti, 2007; Bordalo et al., 2012, 2013). When evaluating hypothetical health outcomes, the OC is less salient because it is intangible, indirect, (Wason, 1968; Frederick et al., 2009), and lacks emotional intensity (“affect-poor”) compared to physical pain (Hsee & Kunreuther, 2000; Rottenstreich & Hsee, 2001). As a result, individuals may pay limited attention to or even ignore these costs. For instance, people may miss their opportunities to prevent specific diseases (Wettstein et al., 2012; Kimball et al., 2020) and only regret it once they turn ill. This neglect of opportunity costs, usually caused by lack of salience implies insufficient risk perception, leading to potential sub-optimal decisions and welfare loss.

Even when people do pay attention to opportunity costs, they may struggle to evaluate numerical information like time duration or probabilities related to health outcomes. This is known as an evaluability problem in decision psychology (Hsee, 1996; Hsee et al., 1999; Hsee & Zhang, 2010; Hsee et al., 2019). It occurs when individuals are unfamiliar with the stimuli (Morewedge et al., 2009), evaluated singly without a reference point for comparison (Hsee, 1996), or when the information is abstract and does not evoke strong emotions (Hsee & Zhang, 2010). Low evaluability reduces sensitivity to numerical data because people cannot easily relate these figures to their actual well-being. This insensitivity may lead to inconsistent preferences or decisions, known as preference reversals (Hsee, 1996; Hsee et al., 1999; Sunstein, 2018) and can result in either underestimating or overestimating risks in various scenarios, leading to biased judgments and suboptimal actions.

We can reasonably hypothesize that OCN is common in health-related judgments and decisions, and we aim to discuss its behavioral impacts. This paper is one of the first to systematically examine whether OCN contributes to the “low-hanging fruit” paradox in preventive health. The cognitive processes in evaluating opportunity costs about health outcomes, and its behavioral consequences, are difficult to isolate in economic analysis. This complexity may explain why previous studies have not formally established this link. Our primary contribution is to incorporate the concept of *opportunity cost neglect* into the health economics literature and provide empirical evidence of its prevalence and consequences in the U.S. population through seven randomized controlled experiments. Specifically, following standard OCN research methods (Frederick et al., 2009; Spiller, 2011), Experiments 1-2 pin down that OCN usually concentrates on failure to foresee the wage losses from sick leave and show that it could be prevalent in a considerable percentage (15-30%) of decision makers. We then link this bias to four common errors in preventive health judgments, each connected to the existing literature.

An obvious yet fundamental consequence of OCN is under-prevention, which directly relates to the “low-hanging fruit paradox.” Experiments 3-4 show that when opportunity costs are not salient, individuals are less likely to choose a preventive measure, even if it is highly cost-effective—a finding consistent with previous literature (Persson & Tinghög, 2020). The other three biased patterns also link to the concurrent literature. First, as shown in Experiment

5, individuals with OCN often show insensitivity to the time horizon of diseases, a pattern linked to duration neglect (Fredrickson & Kahneman, 1993; Morewedge et al., 2009; Alaybek et al., 2022). Second, Experiment 7 showcases considerable evidence on insensitivity to the effectiveness of prevention measure under OCN, which aligns with the literature of probabilistic insensitivity under decision scenarios with rich emotions and no money involved (McGraw et al., 2010; Pachur et al., 2014; Suter et al., 2016). Finally, almost all experiments in this paper suggest that OCN weakens the correlation between people's income and their preventive choice or willingness-to-pay over preventive measures, occasionally reducing it to zero. This goes against standard literature in contingent valuation (CV) (Olsen & Smith, 2001).

We go one step further than documenting the bias. our second main contribution is the development of a practical intervention, "Active Unpacking with Money" (AUM), designed to mitigate OCN in preventive health judgments and improve decision quality. By explicitly reminding individuals of potential wage losses from unpaid sick leaves (*unpacking*) and using monetary values (*with money*) to quantify the costs, AUM effectively enhance the salience and evaluability of time-related opportunity costs. Moreover, reminding people of the financial cost (but not the abstract, total opportunity cost) may have a higher efficacy, because people typically take unpacked (detailed, decomposed to individual components) descriptions more seriously than holistic and abstract ones (Savitsky et al., 2005; Van Boven & Epley, 2003). Finally, because the subject *actively* calculates the loss on their own, the intervention may lead to deeper engagement with the information, enhancing self-perception (Bem, 1972) and enhanced involvement (Muncy & Shebly, 1984; Michaelidou & Dibb, 2008). This combined effect of AUM raises risk perception, improves sensitivity to time and prevention efficacy, and strengthens the correlation between income and willingness-to-pay for prevention, all indicators of more rational preventive decision-making. By offering this effective, easy-to-implement tool, our study contributes to the growing literature on preventive health nudges, a vital area in health economics and policy (Thaler & Sunstein, 2009; Blumenthal-Barby & Burroughs, 2012; Dai et al., 2021; Milkman et al., 2021).

Particularly, this paper's randomization schemes allows us not only to "*diagnose the problem*" in *control groups*, but also to "*offer a treatment*" in *AUM groups*. Furthermore, our experiments include parallel comparison groups and varied versions of AUM, each of which serve as an important benchmark for us to isolate the net effect of enhancing opportunity cost salience and evaluability from other potential cognitive factors. This design provides robust support on our proposed mechanism of the prevalence of OCN and the effectiveness of AUM.

The paper is organized as follows. Section 2 outlines the experimental design and provides an overview of the findings. Section 3 offers an experiment-by-experiment demonstration of the experimental design and their respective main results. Section 4 delves into the implications and limitations of this paper. Section 5 concludes.

2. Experiment Procedures and Results

In this part, we provide more detailed reports of the experimental procedures and main findings

from Experiments 1-7.

Experiment 1: Opportunity Cost Neglect in Prevention Choices

Experiment 1 is designed to empirically test opportunity cost neglect and its solutions. To show more refined evidence, we generated five experimental groups which differ from each other in the way of describing the costs of illnesses and see their effects on people’s risk evaluation.

Experiment 1 was a pre-registered experiment (AsPredicted #186402) conducted on MTurk through CloudResearch from Aug. 14-Aug 21, 2024. 1,026 subjects of MTurk participated in the experiment. After inform consent and eligibility screening⁴, 945 eligible participants were randomly assigned to one of the five groups (Control, Work, Work+Salary, Packed, and Leisure). All responses were included in our analysis.

The participants were asked to imagine being stricken by a respiratory illness adopted from a WHO document, indicating that the illness would last for five weeks and force the patient to stay in bed, implying a five-week sick leave. Then, the participants were told that there existed a fully effective preventive measure that can surely eliminate the possibility of getting sick, and it was priced \$1,600. In short, they faced a hypothetical scenario in which if they did nothing, they would definitely get sick (and face the sick leave); and if they bought the prevention measure, they would stay healthy.

The experimental response was a binary choice, with the subjects having to choose between Option A, “Decline the preventive measure and accept the risk of being sick” (the same description across all five groups) and Option B, purchasing the preventive measure. The description of the “purchase” option varied across five groups, as shown in the following table:

Table 1: Experimental Design for Experiment 1

Treatment Group	Option B Description
Control	Pay for the preventive measure and avoid getting sick
Work	Pay for the preventive measure and avoid getting sick. You can save the three weeks for work .
Work + Salary	Pay for the preventive measure and avoid getting sick. You can save the three weeks for work and protect your salary .
Packed	Pay for the preventive measure and avoid getting sick. You can save the three weeks for other purposes .
Leisure	Pay for the preventive measure and avoid getting sick. You can save the three weeks for leisure .

In Federick et al. (2009), the opportunity costs were described as the “Packed” arm, reminding that the subject would be able to save the time/money for other uses. However, based upon the behavioral discussions above, we hypothesized that mentioning the salary directly would be the

⁴ Aged between 18-65; currently full-time employed, self-employed, or part-time employed.

most effective choice. Accordingly, we designed “Work” and “Work + Salary” groups to test our hypothesis. We also added an arm of “Leisure” to explore whether leisure is also an important element in the opportunity cost neglect patterns in our paper.

We measured the basic demographics (gender, age, employment status) of the subjects, and counted the frequency of choosing Option B in each of the five groups. The estimated likelihood of taking preventive behavior among difference groups are shown in Figure 1.

Figure 1: the Estimated likelihood of taking preventive behavior among difference groups

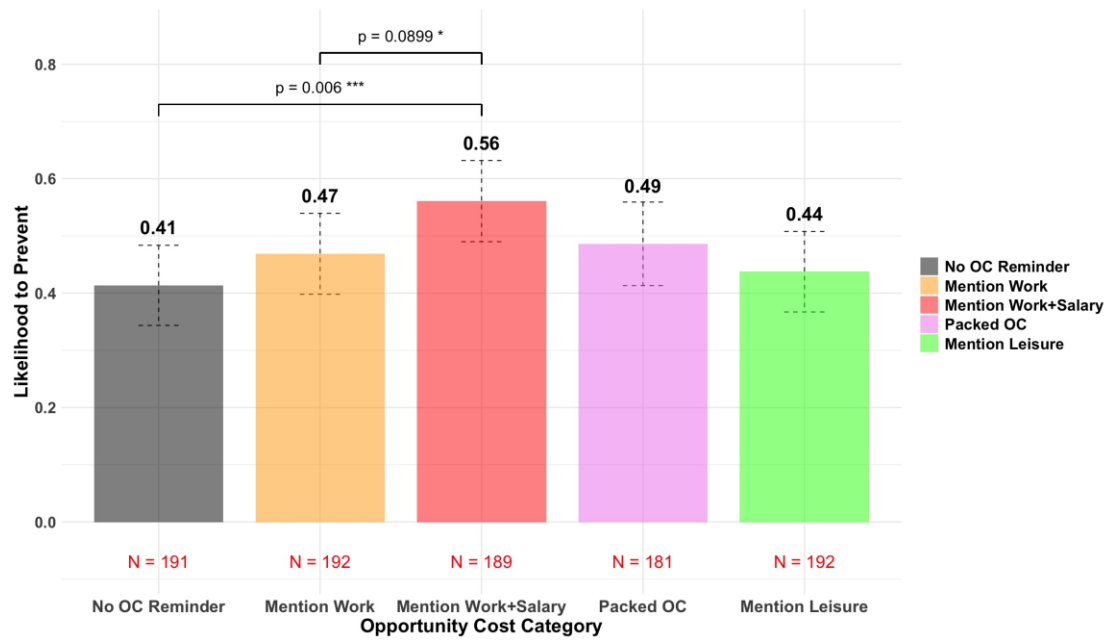


Figure 1A: Acceptance Rates of Prevention Measure across Different Treatment Arms. The error bars denote the standard errors (not standard deviations) of the acceptance rate (likelihood to do the prevention).

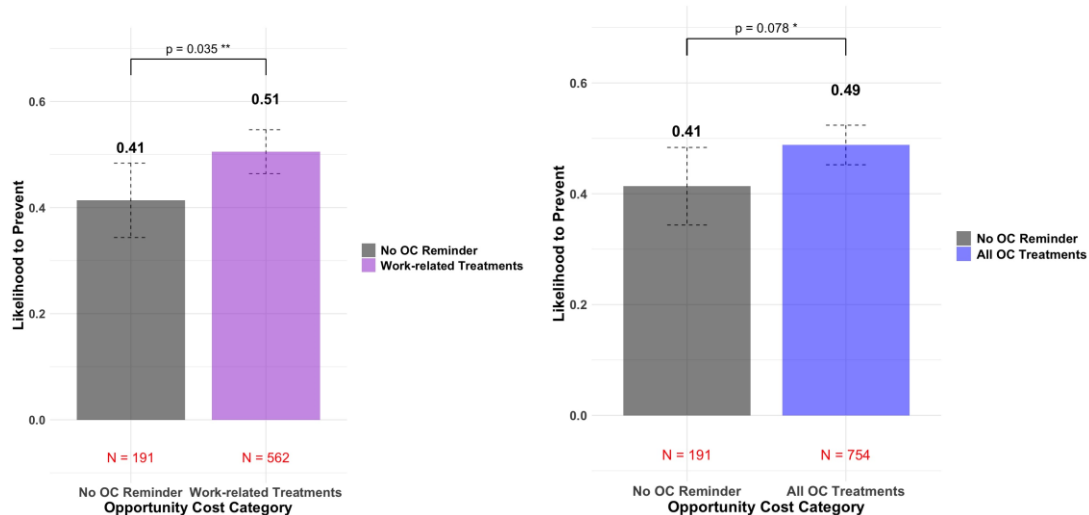


Figure 1B: Work-related OC Treatments Have a Positive Effect on Acceptance Rates

We also perform logit regressions to test our hypotheses. Note that a pairwise z-test is

equivalent to a regression without adding control variables, and some of the important pairwise test results are demonstrated in the Figures above.

Table 2: Main Regression Results and Pairwise Tests about Acceptance Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome Variable	Choosing Option B	Choosing Option B	Choosing Option B	Choosing Option B	Choosing Option B	Choosing Option B	Choosing Option B	Choosing Option B
Setup	Control vs. Each Treatment	Control vs. Each Treatment	Work vs. Work + Salary	Work vs. Work + Salary	Control vs. All OC Treatments	Control vs. All OC Treatments	Control vs. Work-related Treatments	Control vs. Work-related Treatments
Treatment: Work	0.224 (1.09)	0.229 (1.10)						
Treatment: Work+Salary	0.594*** (2.86)	0.606*** (2.90)	0.370* (1.80)	0.408* (1.94)				
Treatment: Leisure	0.0977 (0.47)	0.123 (0.59)						
Treatment: Packed	0.294 (1.41)	0.313 (1.48)						
Treatment Groups					0.301* (1.84)	0.317* (1.92)	0.370** (2.19)	0.385** (2.25)
Demographic controls	NO	YES	NO	YES	NO	YES	NO	YES
N	945	945	381	381	945	945	753	753

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.10$. All t values in parentheses.

The results above suggest the following important findings:

- (1) In comparison to the control group, the Work + Salary treatment is the only opportunity cost reminder with significant ($p > 0.05$) treatment effects in enhancing the prevention rate. This demonstrates the existence of opportunity cost neglect (otherwise there will be no change upon language change), and the most effective means to mitigate this bias is to explicitly mention the time-related opportunity cost in the form of salary loss. This necessitates using an “Unpacking with Money” strategy.
- (2) In comparison to only mentioning work, mentioning salary loss as an addition can arguably ($p = 0.05 \sim 0.08$, marginal significance) increase the tendency to choose Option B. This further justifies that mentioning money will incur a more serious risk perception of the illness.
- (3) Compared to mentioning the opportunity costs about work, the effect of mentioning the opportunity cost of leisure loss is negligible. This is demonstrated by the result that the net effect of including work (Work, Work+Salary, Packed) is significant at 5% level, but no

longer significant at 5% level when adding the “Leisure” treatment into the “all treatments” group. Only mentioning leisure has little effect in changing people’s choice. This validates not using leisure-related treatments in the entire paper.

Experiment 1 replicated the past research (Frederick et al., 2009) and show that the work-related opportunity costs are likely to be neglected in preventive judgments, but can be aroused when missing work and salary loss are directly reminded. On the contrary, mentioning opportunity costs regarding leisure has negligible effect. This study, thereby, sets up a solid foundation for other experiments.

Experiment 2: AUM Mitigates Opportunity Cost Neglect in Prevention Choices

Experiment 1 provided robust evidence that mentioning the sick leave loss from getting sick will effectively remind people of this part of OC and increase prevention intention. However, there is still a question left: does people make this choice based on a careful evaluation of their real costs and benefits, or just a psychological impulse from salient priming? To answer this question, we can apply the behavioral intervention package mentioned in the introduction, Active Unpacking with Money (AUM). Experiment 1B contrasts the standard OC reminders with AUM-assisted OC reminders and explores the special features underlying the cognitive processes with and without AUM.

In this experiment, we delve into the causal impacts of AUM on considering opportunity costs regarding health outcomes. For this purpose, we investigate whether active unpacking of the economic losses from three weeks' sick leave will increase the tendency to make a prevention that costs \$1600.

This experiment replicated the procedures of Experiment 1A except for two differences. First, we only included two groups. The treatment group experienced the AUM procedure before being asked of the binary choice question. The procedure is: (1) The subject was asked to report her last month's income before seeing the choose-one question. (2) The subject calculated the dollar amount lost from the missing three weeks' income. (3) Afterwards, Choice B became, "Pay for the preventive measure and avoid getting sick. You can save the three weeks for work and protect your salary of XX", in which XX is the amount she submitted for the calculation task. (4) The subject chose between Choice A (accept the risk) and B. The control group followed the manners of the “Work+Salary” setup of 1A, followed by the same AUM procedures right after it. This prevents the AUM procedure to impact the binary choice, but we can still observe people’s numeracy and attention by using correctness of task as a signal. We collected 802 effective subjects (subjects who reported their working status as “full-time employed” and aged 18-65) from Amazon Mechanical Turk through CloudResearch from Sep. 10 to Sep. 18, 2024.

The most important feature of this experiment is that, when ignoring other dimensions of losses, the subject would choose to accept the preventive measure if and only if the sick leave loss is over \$1600, or the monthly income is over \$2133. This is a very strong assumption. However, it is a much more conservative and reasonable hypothesis that the treatment group will have a larger acceptance rate than the control group when their income is over \$2133.

Similarly, the relationship should be reversed when the income is below \$2133. Testing people's choices below and above \$2133 can effectively demonstrate that with AUM, the subject may delve into a reasoning style that relies more on the quantitative information of opportunity costs and make a more careful evaluation. In our analysis, one pre-registered confirmatory analysis and four exploratory analyses simultaneously support our story above.

Among all 802 subjects, 398 belonged to the treatment group, and 404 the control group. 570 (71.1%) reported a monthly income of over 2133 dollars. Across the two groups, the correct rate (AUM response and the right answer deviated for ≤ 50 dollars) are 63.9% in the treatment group, and 68.1% in the treatment group. There are no statistical differences ($p=0.21$ for full sample, $p=0.24$ for samples with income $\geq \$2133$) across income level or correct rate across two groups, suggesting that the attention level did not vary across the treatment and control groups.

Result 1: AUM increases the acceptance among wealthier individuals

Results in Column (1)-(3) from Table 3 was conducted based upon our pre-registered analysis (AsPredicted #188644). They investigated the effect of our treatment condition dummies (base = control) on the subsample in which the subjects have a monthly income of ≥ 2133 dollars. Clearly, AUM increases the tendency to accept the prevention measure when the monthly income is larger than \$2133, with the p-value around 0.01-0.03. Specifications of Logit model and linear probability models remain robust.

Table 3: AUM increases acceptance rates among high-income subjects and vice versa

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Acceptance of Prevention	Acceptance of Prevention	Acceptance of Prevention	Acceptance of Prevention	Acceptance of Prevention	Acceptance of Prevention
Income	$> \$2133$	$> \$2133$	$> \$2133$	$< \$2133$	$< \$2133$	$< \$2133$
Model: Probit						
AUM	0.250** (2.31)	0.271** (2.48)	0.278** (2.53)	-0.275 (-1.64)	-0.290* (-1.69)	-0.292* (-1.70)
Log-income			0.205** (2.05)			-0.0277 (-0.34)
Demographic Controls	No	No	Yes	No	No	Yes
Observations	570	570	570	232	232	232

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Due to a potential lack of statistical power, and the complicity of the total cost comparison structures for people with a lower income, we did not preregister the analysis for subjects with income below \$2133. Exploratory analysis (4)-(6) suggested that AUM reduced the tendency to accept the prevention measure in this case, consistent with the theoretical prediction. People realized that the financial loss may be less than the cost of the prevention measure and therefore declined the offer. Yet, we do acknowledge that the welfare implications in this scenario is

ambiguous.

Result 2: AUM still increases the acceptance among wealthier individuals, even mentioning the information on both the work and salary

Table 4, mentioning acceptance rate across different groups, intuitively show the robustness of our findings, clearly suggesting the effectiveness of AUM at different income levels.

Table 4: Acceptance Rate of Prevention Measure in Heterogeneous Groups

Acceptance Rate	Treatment (AUM)	Control (Work + Salary)	Difference	z-score of comparison
Total	58.3%	56.0%	2.3%	0.67
Inc. > 2133	69.7%	60.5%	9.2%	2.31**
Inc. < 2133	33.1%	43.5%	-10.4%	-1.64
Inc. >= 4000	76.0%	62.4%	13.6%	2.85***
Inc. < 2000	31.0%	43.8%	-12.8%	-1.82*
Inc. > 2133 & Correct	73.1%	64.7%	8.4%	1.75*
Inc. > 2133 & Incorrect	62.5%	53.2%	9.3%	1.31
AUM > 1600	73.2%	60.0%	13.2%	3.15***
AUM < 1600	35.4%	47.3%	-11.9%	-2.04**

*p<0.10, **p<0.05, ***p<0.01

The table suggests that AUM robustly increases the acceptance rate of high-income subjects and decreases that of low-income subjects. Also, using the final calculation result as the bar (\$1600) has a slightly higher predictive power than using the initial income, but the difference is slight.

Result 3: Correctly or incorrectly answering the AUM question does not matter

The results in Table 4, along with probit regressions with income and demographic controls, suggest that the treatment effect of AUM does not differ across low-numeracy and high-numeracy individuals as the ATE is almost the same across the two subsamples with correct or incorrect AUM results. This implies that AUM may be effective even among people with low attention or low numeracy skills.

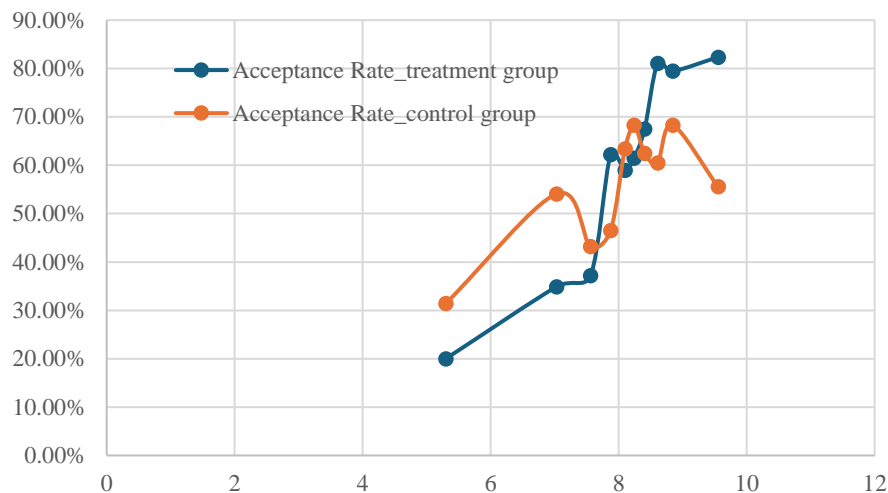
Result 4: Income better predicts acceptance rate in treatment groups

According to many economic and public health theories, rational decision-makers' willingness-to-pay should depend on the income.

The graph above demonstrates the relationship between the logarithm of income and acceptance rate. We can see that in the treatment group, there is a "jumping" of acceptance rate between 7.5 and 8, indicating that \$2133 ($\log 2133 = 7.67$) is a critical value signing the change of attitude. This jumping pattern is much less salient in the control group. However, it is worthwhile to mention that even in the treatment group, the upper bar of the conditional

acceptance rate is still less than 1, indicating that there are about 15-20% “always-decliners” in the subject pool.

Figure 2: The “Jumping” Process of the Relationship between Income and Acceptance



An interaction analysis also suggests that the introduction of AUM increases people’s sensitivity level to their income in a linear fashion. The regression is as below:

$$Pr(\text{Response} = 1)_i = \alpha_1 \text{Trmt}_i + \alpha_2 \text{Logincome}_i + \beta(\text{Trmt}_i * \text{Logincome}_i) + \text{controls}_i + e_i$$

The probit regressions suggest that β is positive with $p=0.018$. All these findings conclude that AUM makes people think of their opportunity cost of sick leaves more seriously and accurately (Frederick et al., 2009).

Experiment 3: AUM Increases Health Risk Perception through Salience

We argued that due to salience and evaluability problems, people have OCN in judging negative health outcomes and thus have an insufficient risk perception, and that AUM is an effective debiasing tool. In Experiments 3 and 4, we can showcase: (1) it is highly likely that OCN will lead to insufficient risk perception; and (2) the effectiveness and psychological mechanisms of AUM in raising risk perception through randomized online experiments.

Experiment 3 is designed to showcase twofold findings. The control group demonstrates that people may have insufficient risk perception due to OCN when the OC is not salient. The treatment group thereby tests the net effect of AUM on health risk perception, and a comparison group helps isolate the cognitive mechanisms of AUM. To capture subjective risk perception, we focus on two variables: (1) the self-reported life impact of a disease, and (2) a willingness-to-pay elicitation for a measure that would surely prevent this disease, which would otherwise surely take place.

Experiment 3 was a preregistered experiment (AsPredicted #126197) conducted on MTurk through CloudResearch on Mar 23rd, 2023. 635 participants on MTurk took the experiment. After informed consent, the participants were randomly assigned to one of the three groups

(control group, Active Unpacking with Money group (AUM) and Pure Information (INFO)). 613 non-zero responses were collected.

All participants were presented with a description adapted from a WHO document. The control group merely saw symptom and duration information: “*The person has a persistent cough and fever, is short of breath, feels weak, has lost a lot of weight. This lasts for three months.*” In contrast, the AUM and INFO groups saw the same description with an additional sentence indicating the sick leave OC information, “*...and has to take unpaid leave and miss three months’ income.*” It is important to clarify one thing here: in this experiment, there may be informational differences between the control group and the treatment groups because getting the aforementioned symptoms does not guarantee sick leave (although very likely). However, there is no informational difference between AUM and INFO groups, which indicates that rational agents should at least have the same risk perception and WTP in these two groups.

Following this, the AUM group was asked to calculate the hypothetical financial loss resulting from losing three months of personal income based on their annual income reported at the beginning of the experiment. The INFO and control groups, however, were asked to perform an unrelated calculation task that was similarly difficult and of comparable numerical scope. This task was designed to prevent any confounding effects of anchoring and adjustment (Epley & Gilovich, 2006) on the results. Accordingly, the AUM and INFO groups only differ in the nature of the calculation task (financial losses vs. a non-pecuniary computation), and the INFO and control groups only differ in the information on unpaid sick leave.

Figure 3: A Comparison of the User Interface of the AUM and Irrelevant Calculation

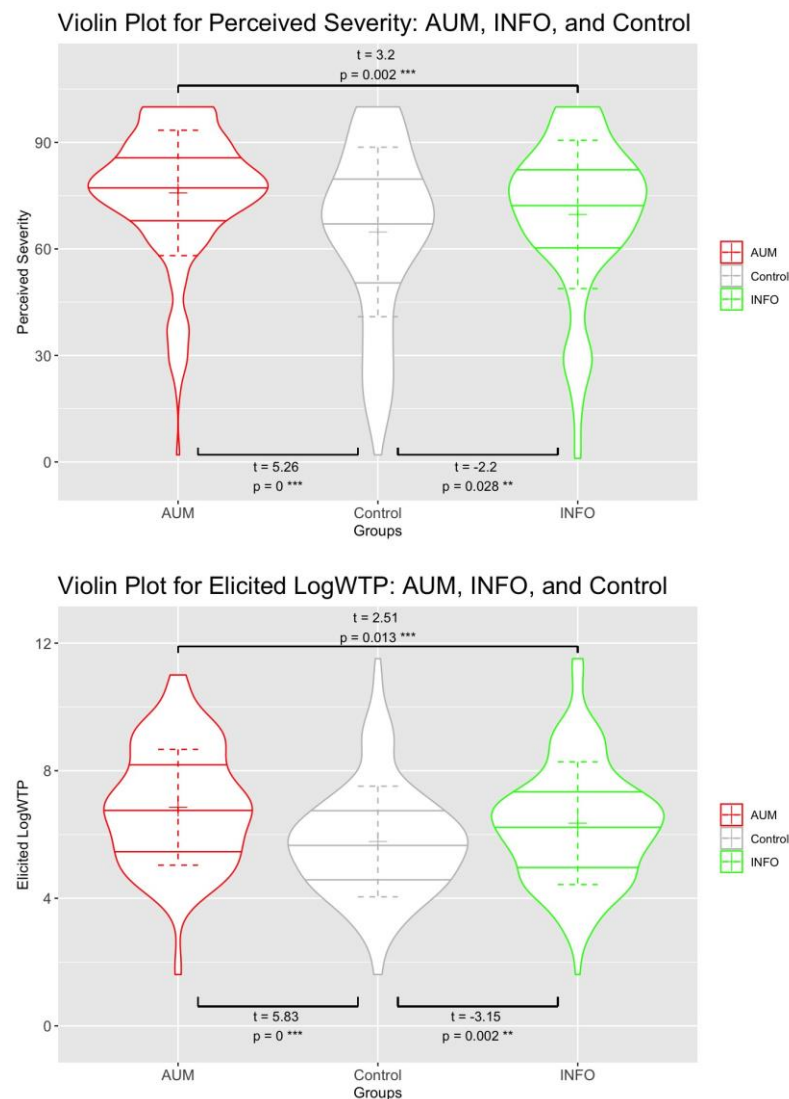
<p>Now, let's do a bit of quick math (you can use the calculator below)! You have reported that your annual income is about \$ 76000.</p> <p>Based upon your annual income status, how much, in \$, would you lose, if you missed three months' income like the statement above? Please write in numbers only, without commas or symbols.</p> <p>(A calculator will appear when you click in the box. Make selections on calculator and hit "Use" to submit.)</p> <input type="text"/>	<p>Now, let's do a bit of quick math (you can use the calculator below)! Annually, there are 75,600 guests coming to a local amusement park.</p> <p>Based on this annual flow data, how many people, on average, will come to this part in the first two months of a year? Please write in numbers only, without commas or symbols.</p> <p>(A calculator will appear when you click in the box. Make selections on calculator and hit "Use" to submit.)</p> <input type="text"/>
<input type="button" value="→"/>	<input type="button" value="→"/>

Afterward, participants were instructed to imagine that the health outcome described in the previous section would occur to them. They then answered questions about the severity rating of the health outcome using a 0-100 slider scale. Subsequently, participants were asked about their willingness-to-pay (WTP), in dollars, for a hypothetical prevention. This prevention would be guaranteed to eliminate the possibility of experiencing the health outcome, which would otherwise surely occur without any preventive measures. The design of this phase aimed to create a conceptual environment where participants could evaluate the negative health outcome without the influence of risk and uncertainty.

After removing extreme outliers⁵, we present two violin plots. These plots depict the responses of individuals in three different experimental conditions, focusing on their WTP (in log form) and Perceived Severity. In this experiment, we mainly focus on logarithms because of their higher robustness against extreme values. We did the balanced tests for the three groups, and random allocation is showcased⁶.

The results are presented as the following violin plot. The base of the logarithm is e . The violin plot indicates the density function at each value on the Y-axis. The solid horizontal lines are 25%, 50% (median) and 75% quantiles. The crossings in center positions are means. The dashed horizontal lines are +1 and -1 standard deviations.

Figure 4: Perceived Severity and Log-WTP for a Prevention in Three Groups



Compared with the control, the INFO group has a significantly higher severity rating of the health outcome ($t(401) = 2.20$, $p=0.03$, Cohen's $d = 0.219$), and a significantly higher

⁵ For WTP-related questions, outliers would have a much larger impact on the result than choice experiments. So, we need to eliminate outliers in the following experiments.

⁶ In all following experiments, balance tests are assumed to be passed and only abnormal results (if any) will be reported.

willingness-to-pay (in log form) for the hypothetical prevention ($t(401) = 3.14$, $p=0.002$, Cohen's $d = 0.313$).

Compared with the control, the AUM group has a significantly higher severity rating of the health outcome ($t(406) = 5.31$, $p<0.001$, Cohen's $d = 0.526$) and a significantly higher willingness-to-pay (in log form) for the hypothetical prevention ($t(406) = 5.82$, $p<0.001$, Cohen's $d = 0.576$).

Finally, the AUM group outperformed the INFO group in increasing people's severity rating of the health outcome ($t(413) = 3.20$, $p=0.001$, Cohen's $d = 0.314$) and people's willingness-to-pay (in log form) for the hypothetical prevention ($t(413) = 2.51$, $p = 0.01$, Cohen's $d = 0.246$).

All of our major findings are robust to adding common control variables, such as age, income, and completion time. The findings in Experiment 2 demonstrate that the AUM procedure significantly enhances the level of the risk perception. Indeed, the median response within the AUM group (\$1000) was four times as high as the Control group (\$250), and twice as high as the INFO group (\$500). It is important to note that these numbers remain significantly lower than a three-month wage loss for the majority of participants. This suggests two key insights: (1) participants did not merely replicate their earlier calculations, and (2) the case over-reporting (reporting a WTP much larger than total potential costs) is negligible. Even with the AUM procedure, participants still underestimated the true magnitude of the potential loss.

Experiment 4: Further Mechanisms of AUM and Health Risk Perception

Experiment 4 was designed as a natural extension of Experiment 3. While Experiment 3 introduced us to the net increasing effects of the AUM process on risk perception, Experiment 4 aimed to dissect these effects in depth. Experiment 4 reveals the individual contributions of salience, evaluability, and active engagement in shaping risk perceptions. Employing a five-arm randomized design, we differentiate the effects of increasing salience, improving evaluability, and giving agency in enhancing people's risk perception.

We adopted the same stimuli (a non-lethal lung disease lasting for three months) and dependent variables (perceived severity and willingness to pay for prevention) as in the previous experiment. Also, unlike the last experiment, we carefully manipulated the expression of information in each group to ensure that participants in the five groups received identical information.

In the Non-salient control group (Group 1), opportunity cost information is mentioned, but its salience was kept minimal. The descriptive text was 'The person has a persistent cough and fever, is short of breath, feels weak, has lost a lot of weight during the past three months, *and has to take an unpaid leave meanwhile.*' Since the sick leave is unpaid, a three-month loss of wages is inevitable. However, this description did not directly mention "salary loss," so the salience of OC is still relatively low in this arm.

In the Salient control group (Group 2), the description was modified to "*. . . and has to take an unpaid leave and miss three months' income.*" This explicit wording enhanced the salience

of salary loss. However, it did not quantify the loss, thus not significantly increasing its evaluability.

In Group 3, the AUM group, we followed the same approach as in Experiment 2. We used the same description as Group 2 but asked the participants to calculate it after seeing the description. It, therefore, accounted for both salience and evaluability. However, the AUM group does not guarantee correct decisions by individuals. Thus, the evaluability might be insufficient for those who make incorrect computations, or even offer a wrong benchmark for WTP elicitation.

To cope with this effect, we added Group 4, “the Full-AUM Group,” which provided an error correction and offered the right way of calculation and the correct answer for those who made a mistake in the AUM calculation. This provides the maximally effective treatment of AUM and offers unique information on the upper-bound treatment effect.

Finally, to separately observe whether agency alone constitutes a part of the mechanism, we included the fifth group. This group also ensured both salience and evaluability. The calculated result was directly displayed on the user interface, eliminating the need for users to manually calculate. The information presented to the users was “**. . . and has to take unpaid leave and miss three months’ income, which is about \$XXXXX according to your annual income.**” This treatment may act as another potential upper-bound benchmark, as it offers the strongest anchoring effect and an authoritative conclusion, which may or may not offset the Active engagement effect.

Experiment 4 used the same dependent variables (Perceived Severity on a 0-100 scale and WTP for guaranteed prevention) as Experiment 3. Demographics, self-reported numeracy (Fagerlin et al., 2007; Zikmund-Fisher et al., 2007), and economic resilience information were also collected⁷. This experiment was conducted on MTurk through CloudResearch between July 5th and July 14th, 2023, with 671 subjects completing the experiments. To minimize the noise from insufficient attention and extreme outliers, the main analysis drops the subjects with abnormally low income⁸, extremely values of willingness-to-pay elicitation⁹, insufficient total response time (<120s), or potentially inattentive response in numeracy scales (all reporting 1 or 6). These exclusion criteria led to 490 core responses. In a robustness check, where the exclusion criteria are stricter¹⁰, we obtained 636 effective responses.

We analyze the results from three perspectives. Firstly, we employ different model specifications and observation inclusion criteria. Our aim is to compare the most comprehensive Full-AUM process with the average severity ratings and LogWTP of the other four groups. We also conduct specific pairwise comparisons to determine the relative importance of the three different mechanisms. Consequently, we perform exploratory heterogeneity analyses. Our aim is to examine whether the proposed mechanisms have stronger or weaker effects in specific subgroups with different socioeconomic backgrounds or

⁷ We asked whether the participant would have enough cash, or money in your checking/saving account to cover a \$500 expense if the participant encountered an emergency expense. If the participants answers “Yes” the same question will be asked about a \$3000 expense.

⁸ Less than or equal to \$10k a year

⁹ <=\$50 or >=\$1M

¹⁰ WTP<=\$50 or >=\$1M, Income \$5000/yr, response time <90s

psychological characteristics. This analysis aims to understand the potential variations in the effects of the mechanisms across different populations. Finally, we explore alternative mechanisms and conduct robustness checks to demonstrate why they are unlikely to significantly impact our results. This evidence underscores the robustness of our findings. It supports the argument that these alternative mechanisms are unlikely to compromise the validity of our conclusions.

Figure 5: Violin Plot for Log-WTP for a Prevention in Five Groups

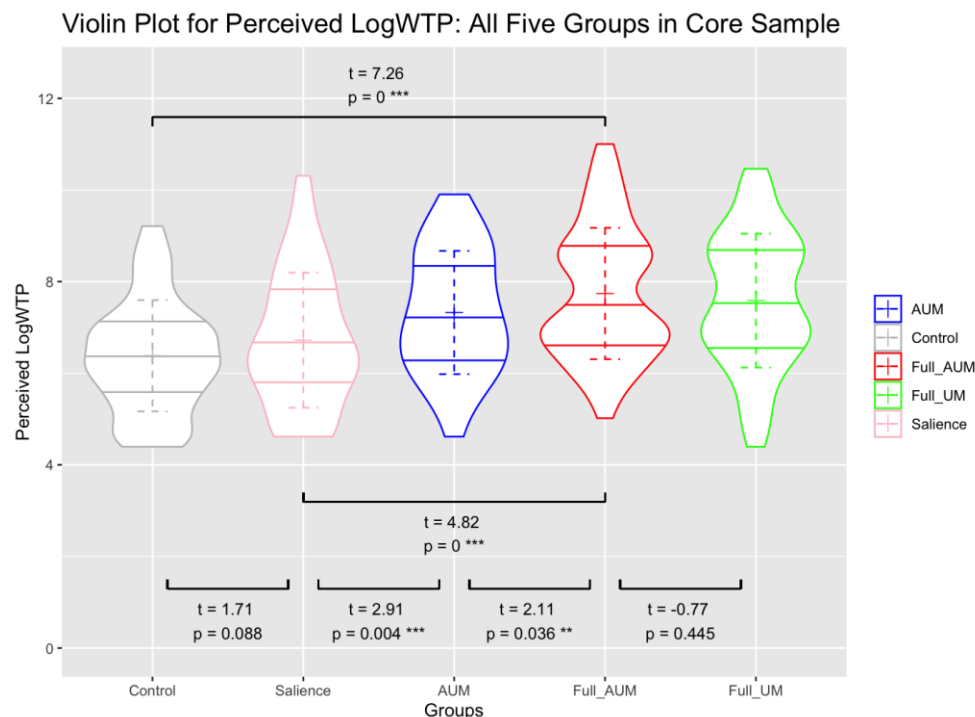
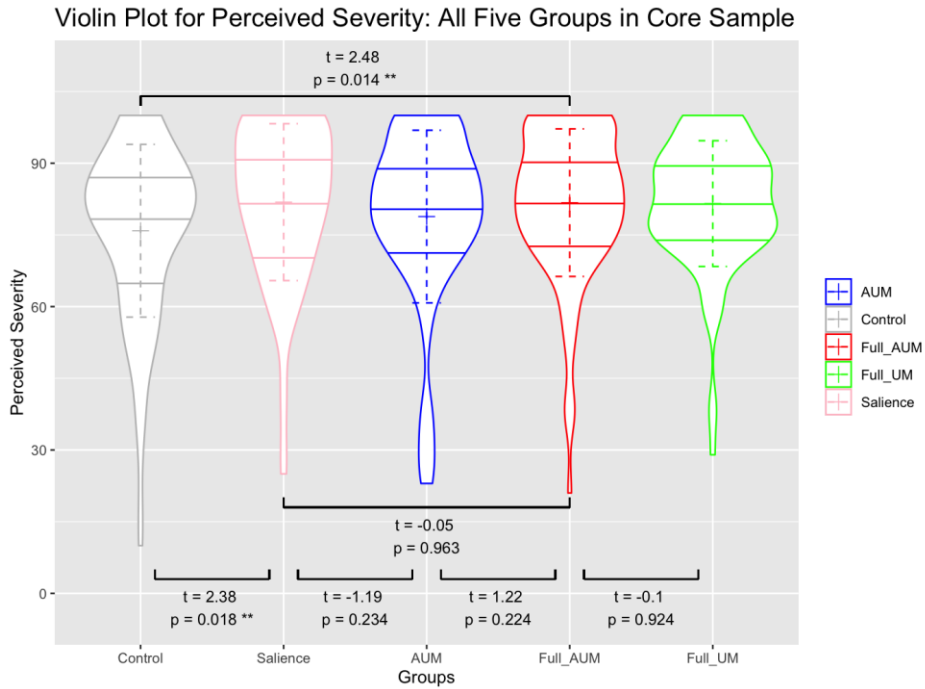


Figure 5 reveals that the full AUM process yields the highest average Log-WTP. It is strongly higher than the two control groups that do not mention monetary loss. For instance, in terms of median, the WTP value in the AUM group is about fourfold of those in Control and Salience groups. It is also significantly higher ($p < 0.05$ in the core sample ($N=490$), approximately 0.10 in the full sample ($N=636$)) than the incomplete AUM group. It is slightly higher (statistically insignificant) than the UM group, where the answer is directly provided to the user. This analysis further demonstrates the statistical significance of the AUM effect and its substantial economic significance.

Moreover, it indicates that the net impact solely from Active engagement is not substantial or that the positive impact of Active engagement may be offset by the authority effect and/or anchoring effect of directly providing the answer and a more pronounced anchoring effect. Pairwise comparisons between the groups mentioning amount or not indicate that numbers matter; they have set up a good benchmark for people to file in their WTP for prevention, though the existence of other biases may still block people from inputting a sufficiently large amount. This is clear evidence for the evaluability effect, which is more obvious when combining our finding in Experiment 2 that pure anchoring did not significantly matter. Finally, pairwise comparisons show that for WTP, a money reference is fundamental, while the direct salience

effect is relatively limited.

Figure 6: Perceived Severity for the Disease in Five Groups



However, when it comes to severity rating (Figure 6), the differences are lower across groups. The only group with a significantly low severity rating is the non-salient control group. This shows that the salience effect plays a more crucial role when the dependent variable is subjective severity. Combining the analysis on Log-WTP and severity in Experiments 2 and 3, we can reach the conclusion that both salience and evaluability play crucial roles in shaping risk perception, but their dominance varies based on the outcome measure. Salience seems more influential for subjective severity ratings, while evaluability has a more pronounced effect on WTP. Nevertheless, the evidence effects of Active engagement may be thin if we offer the strongest non-active intervention (directly giving the numerical answer). To further investigate the mechanisms and check the robustness, we conduct heterogeneous analyses by interacting with our crucial pairwise comparisons such as income, economic resilience, self-reported numeracy, and correctness in AUM calculation. No strong and robust interaction effect is detected.

Experiment 5: OCN Leads to Duration Neglect and AUM Mitigates the Bias

Experiments 3 and 4 discussed how AUM helps enhance the risk perception for diseases by resolving the opportunity cost neglect problems regarding preventive health through salience and evaluability effects. In the following three experiments, we will show that (1) When the opportunity cost is not emphasized, OCN may lead to insensitivity to important numerical information and therefore lead to “preferences” that cannot be rationalized, and (2) AUM not only increases the level of health risk perception but also the sensitivity to the numerical differences regarding health risks (thus making the evaluation more “rational”). This is mainly

through the evaluability effects. Particularly, Experiment 5 and 6 focus on duration neglect, and Experiment 7 studies probability insensitivity.

Duration neglect (time horizon insensitivity) is a commonly detected decision bias that the evaluation of unpleasant experiences responds insufficiently to time duration (Fredrickson & Kahneman, 1993; Holyoak & Morrison, 2005; Morewedge et al., 2009), and this insensitivity is particularly stronger for unfamiliar scenarios (Morewedge et al., 2009). However, the real impact and course of many health issues are closely related (or even directly proportional) to duration, considering factors such as medical expenses for certain treatments or wage losses due to sick leave. In the context where these losses play a significant role, it is necessary to consider the duration factor when assessing potential health consequences to protect their own interest. If people exhibit significant duration neglect when faced with these hypothetical scenarios, they may adopt inadequate or excessive preventive measures, leading to welfare losses.

Experiment 5 and Experiment 6 employed both between-subject and within-subject (between-subject analysis still available) experimental designs, respectively, to explore the alleviation of duration neglect through AUM. We provided robust evidence to demonstrate that AUM is indeed effective in addressing duration neglect. Furthermore, we discussed why such improvements will likely lead to welfare improvements.

We designed a 2×3 factorial design to separate out the effect of pure calculation (priming a calculative mindset) and the direct effects of AUM. In the control group, we investigated the time sensitivity with a description without highlighting the opportunity costs. In the comparison group (Calc), we extracted the effect of a calculative mindset. In the treatment group, we used the AUM intervention to improve opportunity cost consideration.

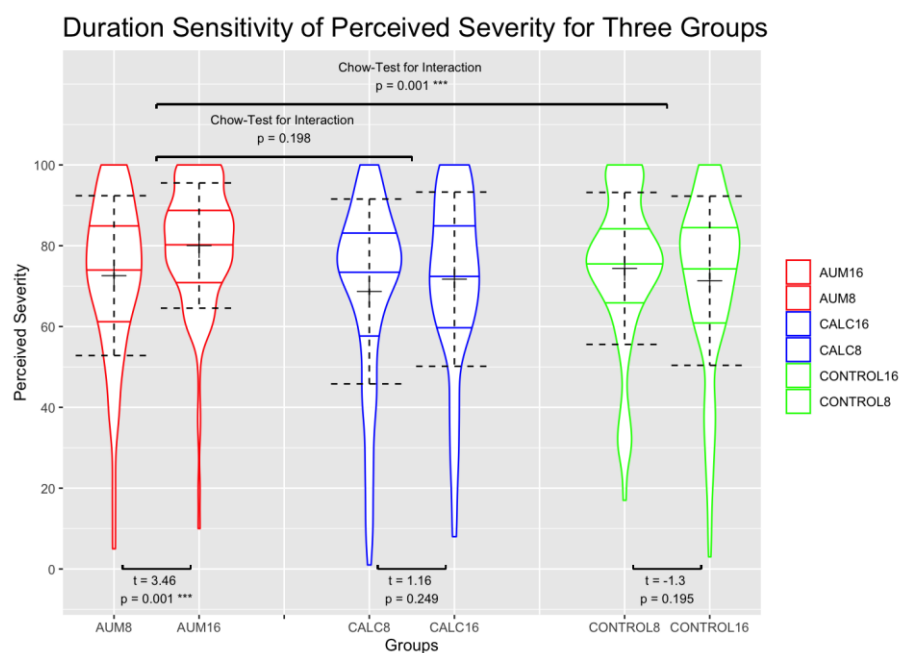
Experiment 5 was conducted on MTurk through CloudResearch, and the data was collected on Apr. 3, 2023. After informed consent, participants were randomly assigned to one of the six groups (Control-8, Control-16, Calculation-8, Calculation-16, AUM-8, and AUM-16). 959 participants took part in the experiment, and we acquired 846 effective responses after eliminating ineligible and potentially inattentive (response time < 75s) or extreme responses ($WTP < \$50$ or $> \$500K$).

Every participant saw a description of 8- or 16-week-long Angina Pectoris adapted from the WHO document. The four arms' participants in Control and Calculation groups saw the description with only symptom and duration information. However, the two AUM groups saw the same description plus a sentence showing information about financial losses. Then, the AUM group was asked to calculate the hypothetical financial loss from losing three months' personal income based on the income elicitation at the beginning of the experiment. The Calculation groups, designed to separate the potential mathematical thinking priming effects, did an irrelevant placeholder task which is the same as that in Experiment 2. The control group did no calculation. The Calculation groups and Control groups did not see descriptions above unpaid sick leave. In this experiment, we allowed for information difference because we intend to study this effect as if it is a real-world comparison between a description without mentioning money and an AUM scenario.

After the treatment, participants imagined the hypothetical scenario that the health outcome would occur to themselves and elicited their perceived severity and WTP for a guaranteed preventive measure following Experiment 3. Necessary demographics were collected.

We begin by conducting a pairwise check on the time duration sensitivity across the three pairs of comparisons. Using T-tests, we found that the time horizon differences in the Control and Calculation groups did not result in any statistically significant differences in severity perception (mean (Control8) = 74.4, mean (Control16) = 71.3, $t=-1.30$, $p=0.19$; mean (Calculation8) = 68.7, mean (Calculation16) = 71.7, $t=1.16$, $p=0.25$) and the logarithm of WTP for prevention (Log-WTP) (mean (Control8) = 6.67, mean (Control16) = 6.62, $t = -0.32$, $p = 0.75$; mean (Calculation8) = 6.69, mean (Calculation16) = 6.73, $t=0.255$, $p=0.80$). This shows that without mapping with money, consumers may show insensitivity to the time duration of an unfamiliar disease in a hypothetical scenario. Moreover, there is evidence that this insensitivity cannot be mitigated by merely priming a calculative mindset. Hypotheses 1A and 1B are rejected. On the contrary, we find that the AUM treatment was effective. The t-tests showed significant horizon sensitivity in both severity perception (mean(AUM8)=72.9, mean(AUM16)=80.0, $t=3.46$, $p<0.001$) and Log-WTP (mean(AUM8)=7.07, mean(AUM16) = 7.64, $p=0.014$).

Figure 7: Perceived Severity and Log-WTP for a Prevention in Three Groups



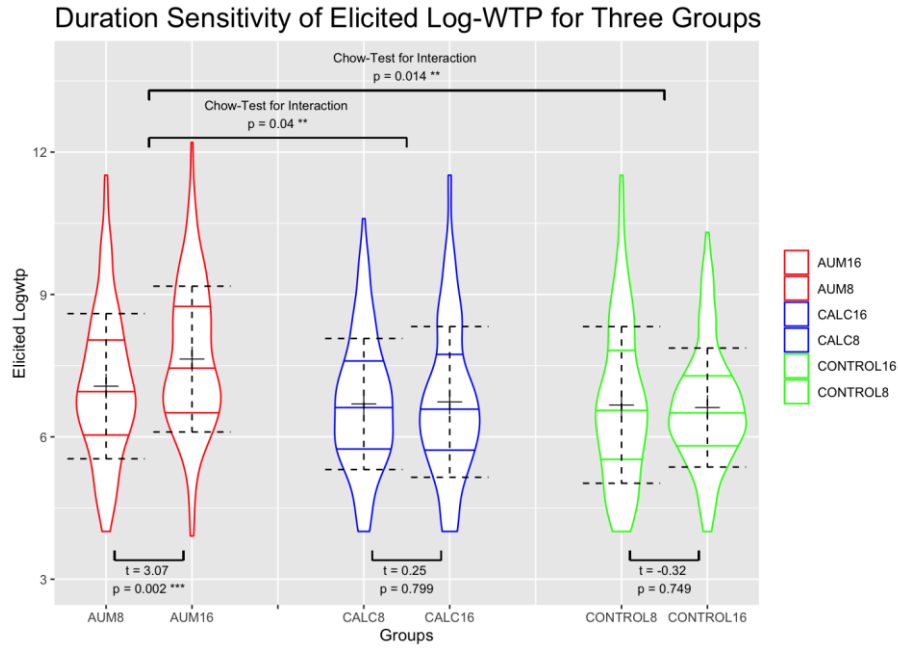


Table 5. Interaction Analysis (Chow-Test) of AUM's Effect on Duration Sensitivity

	AUM vs. Control				AUM vs. Calculation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	LogWTP	Severity	LogWTP	Severity	LogWTP	Severity	LogWTP	Severity
AUM x Duration	0.626** (2.46)	10.50*** (3.29)	0.653*** (2.64)	9.599*** (3.03)	0.526** (2.06)	4.40 (1.29)	0.478* (1.91)	3.07 (0.90)
Duration = 16w	(0.06)	(3.05)	(0.11)	(2.64)	0.04 (0.25)	3.04 (1.27)	0.06 (0.37)	3.70 (1.56)
AUM	0.395** (2.23)	(1.79) (-0.80)	0.395** (2.29)	(0.91) (-0.41)	0.376** (2.07)	3.92 (1.62)	0.380** (2.13)	5.079** (2.09)
Economic Resilience			0.341*** (3.94)	-2.99*** (-2.70)			0.321*** (3.62)	-2.820** (-2.33)
Health Status			(0.04)	(0.44)			0.03 (0.39)	-1.796* (-1.81)
Log-Income			0.118* (1.69)	2.144** (2.41)			0.12 (1.62)	0.59 (0.57)
Age			0.0179*** (3.70)	0.187*** (3.03)			0.0138*** (2.76)	0.138** (2.02)
No Paid Leave			0.364** (2.20)	1.96 (0.93)			0.345** (1.97)	1.65 (0.69)
Paid Leave>=3 Months			0.24 (0.98)	-5.913* (-1.86)			0.447* (1.96)	(0.42) (-0.14)
Constant	6.672*** (54.38)	74.39*** (48.25)	3.893*** (4.97)	51.49*** (5.14)	6.692*** (52.40)	68.69*** (40.27)	3.826*** (4.56)	68.43*** (5.98)
Observations	560	560	560	560	558	558	558	558

t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01

To ensure robustness, we evaluated the statistical significance of the interaction term using 2x2 comparisons for severity, both with and without demographic control variables. The results suggest that except for the perceived severity rating of the AUM-Calculation comparison, all regressions generate a positive interaction effect, indicating a relatively stable causal relationship between AUM and time duration sensitivity. This relationship is robust to adding various control variables. Results are shown in Table 5.

Experiment 5 showcases that people may exhibit strong duration neglect in regular, money-free judgments regarding preventive health. This insensitivity is arguably deviating from optimal decisions and will make decision-makers insensitive to information regarding time duration, which may be economically and physically important for consumers. Plenty of evidence shows that AUM helps mitigate this effect. However, the findings in Experiment 5 are purely between subjects. People were exposed to only one stimulus in the experiment, which corresponds to the separate evaluation case as mentioned in past studies (Hsee, 1996; Zikmund-Fisher et al., 2004). In the real world, there are possible cases in which people may compare their choice with other alternatives (joint evaluation), and in the next experiment, we investigate our intervention's effectiveness within subjects, which resembles joint evaluation scenarios.

Experiment 6: AUM Increases Time Sensitivity: Within-subject Evidence

Experiment 6 primarily acts as a within-subject extension of Experiment 5. A within-subject variation is helpful for us to under the effects of opportunity cost neglect and the AUM intervention in joint evaluation scenarios, where it is possible to make comparisons among the alternatives. Simultaneously, it can further illustrate our sensitivity narrative on a broader numerical scale. We explore participants' willingness-to-pay for a guaranteed preventive measure against Angina Pectoris, examining varying time horizons of 5, 7, 10, and 15 weeks.

We posit that exposing subjects to these four scenarios can enhance within-person sensitivity to the time horizon through the AUM procedure. From a theoretical standpoint, the within-person evaluation represents a joint evaluation (JE) scenario (Hsee, 1996; Hsee & Zhang, 2010), where individuals are anticipated to exhibit heightened sensitivity to time horizons compared to separate evaluations. We further hypothesize that the AUM process will amplify within-person sensitivity during joint evaluations. In other words, the AUM practice is expected to magnify the effects observed in joint evaluations. Theoretically, this expectation stems from the idea that monetary values provide participants with a tangible reference, aiding them in formulating willingness-to-pay reports and comparing relative severities across different JE scenarios. We depict the within-subject WTP response function to the time duration, both with and without the AUM practice. Additionally, we analyze the between-subject pattern to both extend and validate the findings of Experiment 6. Since participants were initially unaware of subsequent questions with varying time horizons, their initial responses can serve as a between-subject measure for time horizon sensitivity under separate evaluations. Certain factors, such as the experiment's suggested duration of 4-5 minutes, might lead participants to suspect the existence of other groups. Thus, we primarily interpret the between-subject findings as both an extension and a robustness check of our results.

Experiment 6 was conducted on MTurk through CloudResearch, and the data was collected between May 23rd and June 2nd, 2023. 1200 Participants participated in this experiment, and we finally got 877 effective responses after eliminating duplicates, potentially inattentive (completion time <120s) subjects, and subjects who had reported at least one extreme value that may be significant outliers (income<\$1k or >\$1M), too extreme willingness-to- pay (<\$50 or >\$500K), too extreme ratings (0 or 100 in severity rating).

During the survey, we gathered data on participants' annual individual income, demographics, and basic economic conditions. As in Experiment 4, each participant was presented with a description of Angina Pectoris, adapted from a WHO document, detailing durations of 5, 7, 10, or 15 weeks. Apart from the duration, descriptions within each group remained consistent. Participants in the four Control groups saw the description with only symptom and duration information. In contrast, those in AUM groups received an additional sentence about potential financial losses. Then, the AUM group did the same calculation procedures as in Experiment 5, and the Control groups did no calculation. Finally, subjects reported their severity rating of these health conditions and elicited their WTP for a guaranteed preventive measure.

This experiment examines if AUM heightens participants' sensitivity to illness duration when presented with varying disease duration information. Our initial test determines whether there is a statistically significant difference in the "sensitivity coefficient" between the AUM and control groups. Mathematically, this is equivalent to the following Fixed Effect Regression:

$$\text{LogWTP}_{i,l} = \alpha_1(\text{length}_{i,l} \times \text{AUM}_i) + \alpha_2 \text{length}_{i,l} + \alpha_3 \text{AUM}_i + FE_i + \epsilon_{i,j}$$

In the aforementioned regression, the interaction term arises from the product of time length and the AUM treatment. The regression coefficient α_1 reflects the main treatment effect.

The graphs in Figure 8 indicate two key insights: (1) A joint evaluation setting, where participants can readily compare alternatives, leads to an enhanced duration sensitivity even when the OC is not salient, and (2) within this joint evaluation, AUM further amplifies this sensitivity. Following standard procedures, we define the elasticity of WTP with respect to the time horizon as:

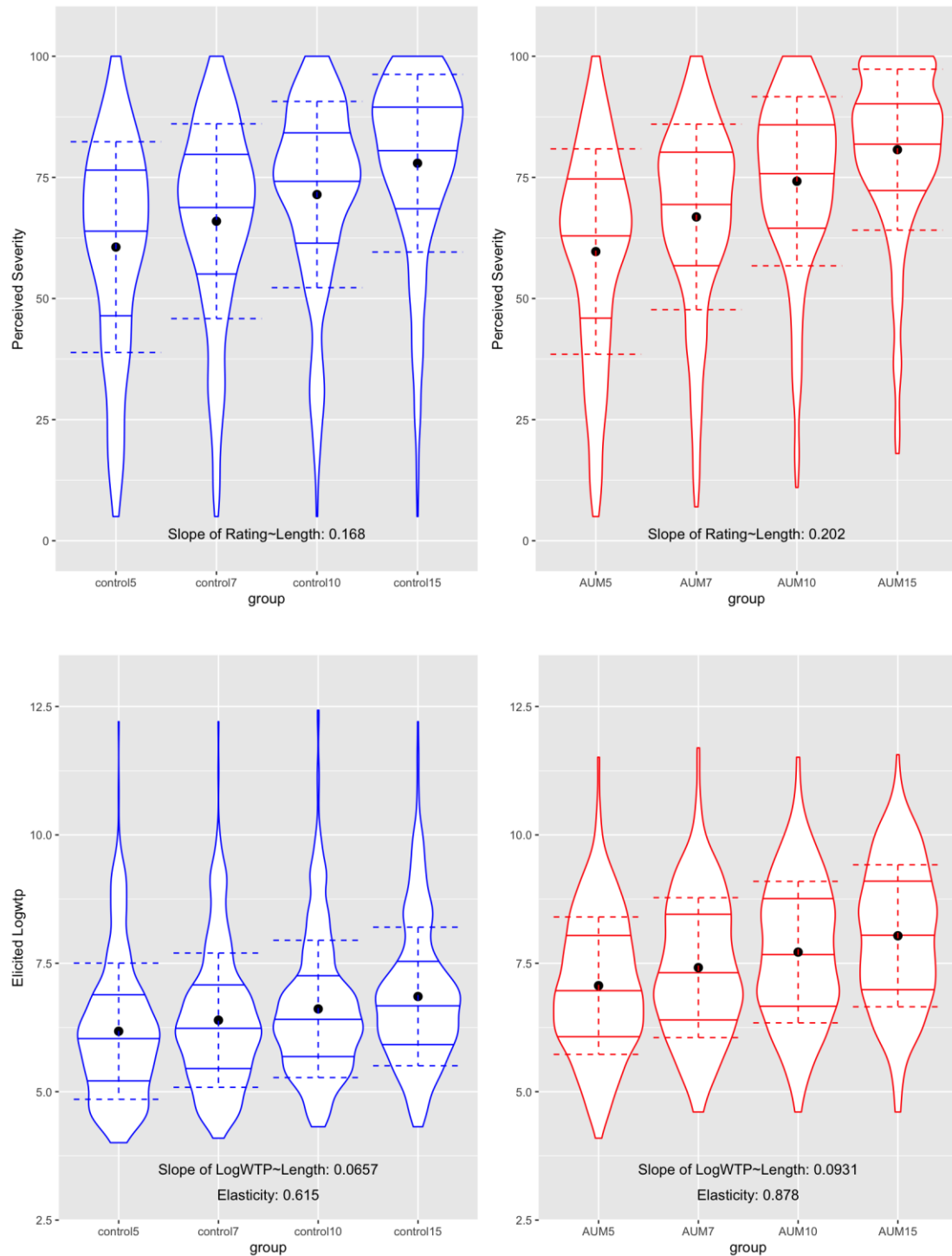
$$e_{WTP,t} = \frac{\partial \log(WTP)}{\partial \log T}$$

This can be estimated by regression $\log(WTP)$ against $\log(time)$, incorporating within-subject control variables. We reveal that this elasticity rises from 0.615 to 0.878 with the introduction of AUM, a statistically significant difference ($p < 0.001$). When shifting to perceived severity as the dependent variable, the difference in sensitivity persists, albeit with diminished numerical magnitude and statistical significance ($p < 0.05$).

Another crucial metric within subjects is response monotonicity. Assuming constant factors such as disease severity, a rational individual's willingness-to-pay for prevention should consistently rise with extended disease duration. Upon examining participants' response patterns, we observed that in the absence of AUM, only 35.3% of reported WTP sequences exhibited a strict increase from 5 to 15 weeks. AUM elevated this rate to 46.8% ($t=3.48$,

$p < 0.001$). Adopting a more lenient, non-strict monotonicity criterion, the rates still saw a notable rise: 78.4% for those without AUM and 84.7% for those with AUM ($t=2.41$, $p=0.016$). This result compellingly indicates that the AUM intervention heightens participants' sensitivity to disease duration.

Figure 8: Perceived Severity and Log-WTP for a Prevention in Four Groups



As a concluding step, we conducted a between-subject robustness check to complement the findings of Experiment 5. Given that participants faced the four questions in a randomized sequence across distinct screens, it's plausible they were unaware of other groups during their initial elicitation task. Therefore, by considering only the participants' initial responses, we can approximate a between-subject analysis. The between-subject analysis revealed that the elasticity of willingness-to-pay concerning the time horizon was 0.23 (non-significant) in the control group. In contrast, this elasticity was 0.74 in the treatment group ($p < 0.001$), with the Chow test confirming a significant difference ($p < 0.05$). This is an effective robustness check of Experiment 4, underscoring AUM's overall efficacy in counteracting duration neglect.

Experiment 7: AUM Mitigates Probability Insensitivity

A notable limitation of Experiments 3-6 is the assumption that preventive measures are guaranteed to be effective, which realistically only applies to specific cases like vaccines offering lifetime immunity, such as the measles vaccine. In many cases, preventive measures are not guaranteed to be effective; rather, they reduce the risk of disease onset probabilistically. For instance, the COVID-19 and influenza vaccines have efficacy rates that range from 60% to 95%. Standard economics literature would predict that the efficacy rates should be a key determinant of people's WTP.

However, when the OC is non-salient, people's perception towards a disease may concentrate on the physical and affect-rich components as our previous experiments suggested. In this case, previous literature predicted probabilistic sensitivity due to emotion-richness (Pachur et al., 2014; Suter et al., 2016) or a lack of measurable money amount (McGraw et al., 2010). To investigate the impact of OCN on probabilistic perception, and the role of AUM in probabilistic preventive decision-making, we designed Experiment 7. The goal of this experiment is to examine the impact of AUM on decision-makers' sensitivity to varying efficacy rates, particularly in terms of their willingness-to-pay for preventive measures.

In Experiment 7, we focused on Angina Pectoris, the same disease examined in Experiments 5 and 6, and maintained a constant potential duration of three months. Our numerical settings were based on prospect theory. Prospect theory posits that individuals are overly sensitive to changes in extreme probabilities (close to 0 or 1) while showing insufficient sensitivity to changes in intermediate probabilities (Gonzalez & Wu, 1999). To avoid interference between decisions made at extreme and intermediate probabilities, we set the upper and lower limits for the disease occurrence probability at 80% and 20%, respectively. In this setting, we hypothesized that people's decisions within this range will always exhibit insufficient probabilistic sensitivity. Simultaneously, we hypothesized that AUM can mitigate this bias, enhancing sensitivity to probability changes.

We employed a 2x4 factorial design similar to that of Experiment 6. In this experiment, all participants were informed that the likelihood of contracting the disease was 80%, with a duration of three months. Participants were then randomly assigned to either one of the four experimental groups or one of the four control groups. To better isolate the effect of AUM, we implemented a strong control measure: both the AUM and control groups received identical

information about a potential loss of three months' income. The only difference was that the AUM group was asked to calculate the exact financial loss equivalent to three months' income, whereas the control group was not. This means that the OC is emphasized but not monetized in the control group, with a higher salience than most real-world cases.

Each participant was presented with four different preventive measures, each having a different efficacy rate. These measures were designed to reduce the risk of contracting the disease by 20, 30, 40, and 60 percentage points, translating to reduced probabilities of 60 percentage points (pp), 50pp, 40pp, and 20pp, respectively. Participants were asked to state their WTP for each of these preventive plans. The presentation order of these measures was randomized for each participant. As in Experiment 6, in this experiment, we can conduct a within-subject analysis for the full sample with the Fixed Effect model. Additionally, we can perform a between-subject analysis using the first WTP value reported by each participant.

The analytical approach for this experiment differs somewhat from the previous ones. Neoclassical health economics typically assumes that individuals act based on expected utility and quasi-linear utility (Mas-Colell et al., 1995). This suggests that, when outcomes are constant and only probabilities change, a rational individual's WTP should be proportional to the changes in probability values. Therefore, it is theoretically justified to use raw WTP values instead of logarithms in the main regression. The regression function for within-subject analysis is as follows:

$$WTP_{i,l} = \alpha_1(reduction_{i,j} \times AUM_i) + \alpha_2reduction_{i,j} + \alpha_3AUM_i + FE_i + \epsilon_{i,j}$$

in which i denotes the i -th participant, and j denotes the preventive measure seen by the participant. For the between-subject we exclude the subscript j from the regression, as it considers only the initial response. In this scenario, we incorporate subject-level controls denoted by $Controls_i$. The between-subject regression is as follows:

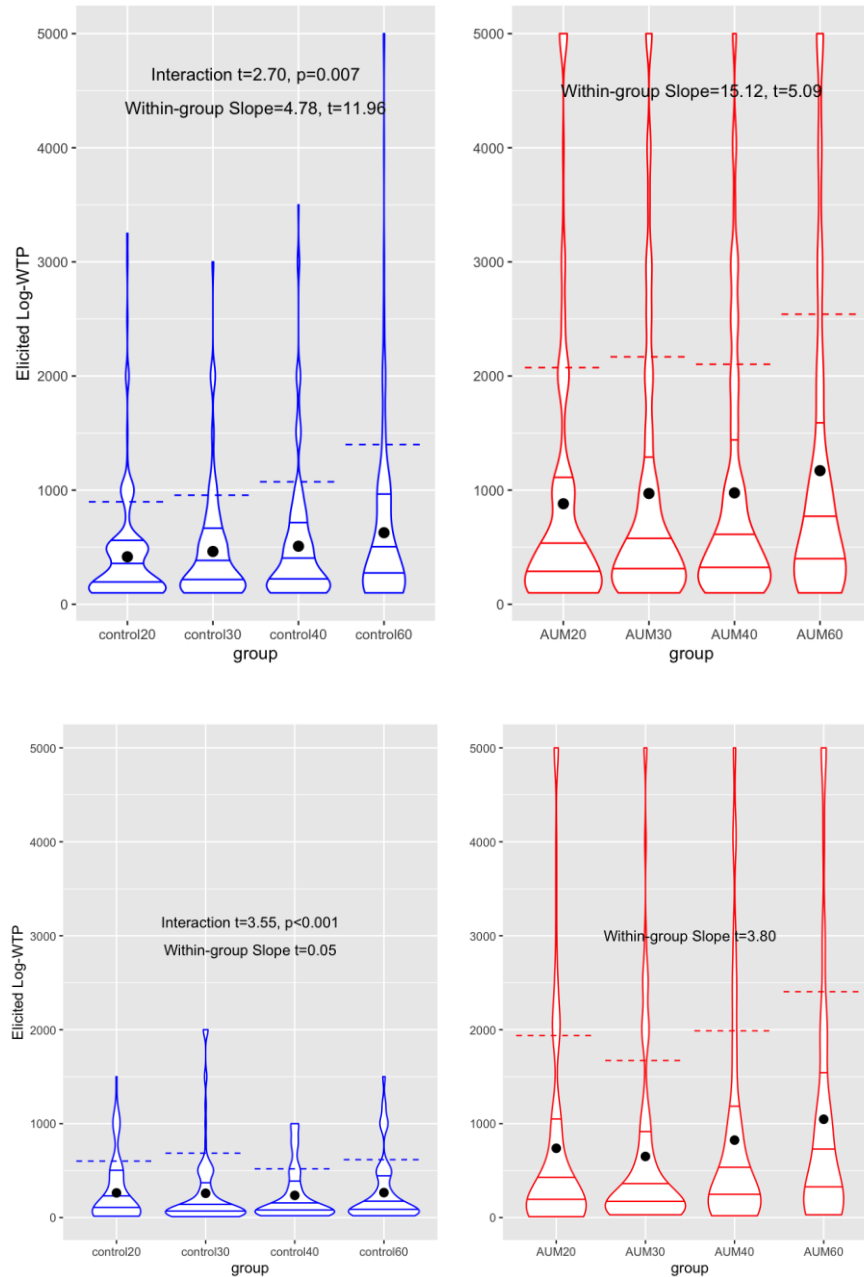
$$WTP_i = \alpha_1(reduction_{i,j} \times AUM_i) + \alpha_2reduction_{i,j} + \alpha_3AUM_i + Controls_i + \epsilon_{i,j}$$

We commenced our data collection for this experiment on July 28, 2023, and concluded it on August 8, 2023. Our sample comprised 1,136 compliant individuals. After excluding plausibly inattentive samples¹¹, we were left with 957 participants. Since the baseline analysis of this study uses WTP rather than Log-WTP as the dependent variable, it was necessary to eliminate outliers in a more systematic way. Thus, all samples with first responses falling below the 10th percentile or exceeding the 95th percentile were excluded, yielding a final sample of 850 individuals.

The ensuing graphs illustrate the results of this experiment, encompassing both within-subject and between-subject analyses.

¹¹ completed in less than 90 seconds, or WTP <= \$1

Figure 9. Log-WTP for a Prevention in Four Groups



The results showcase patterns that share some common features with Experiment 6. In the separate evaluations, as reflected in the between-subject analysis, there's a notable lack of sensitivity to the preventive measure's effectiveness without AUM involvement. Simultaneously, many participants reported extremely low WTP values. Such insensitivity to probability cannot be rationalized by ANY utility function, implying irrational behavior. Our findings highlight that AUM effectively mitigates this issue, significantly enhancing participants' sensitivity to probabilities.

As in Experiment 6, joint evaluation, as depicted by the within-subject analysis, enhances sensitivity to probabilities. There is also significant evidence that AUM groups lead to higher sensitivity than control groups in this condition, but the effect size seems smaller than in

separate evaluation.

It is noteworthy that the WTP responses exhibit considerable skewness, suggesting a robustness check with logarithms. When expressing both WTP and probabilities in logarithmic forms, the interaction term remains significant in the between-subject analysis ($t=2.55$, $p=0.011$). However, the interaction term in the within-subject analysis is not significant ($t=0.11$, $p=0.91$). Based on these findings, we posit that the between-subject results are notably robust, whereas the within-subject analysis yields a less pronounced treatment effect, lacking significance across all regression configurations..

Our observations indicate that while the between-subject treatment effects are notably robust and pronounced, the within-subject treatment effects appear more subdued. We theorize that this discrepancy might stem from the evaluability of probabilistic data and individuals' interpretation of probability within the framework of Expected Utility Theory. Once the participants engage in joint evaluation, the distinctions among probabilities like 20%, 30%, 40%, and 60% become glaringly clear. Within this context, irrespective of the actual outcome, the prominence of the numerical data in the outcome is significantly eclipsed by the inherent salience of the joint evaluation, making the treatment effect somewhat muted. On the other hand, in separate evaluation scenarios (as in between-subject conditions), the interpretability of probability data in Experiment 6 probably falls short of that of disease duration data, primarily due to the non-intuitive nature of prevention efficacy figures. Hence, without a comprehensive understanding of the outcome, participants lack a foundational reference for assessment, prompting them to offer responses that are not only significantly low but also lack sensitivity to probability variations. However, when individuals compute economic losses as part of the outcome, it assists them in estimating the expected magnitude of the loss, thereby markedly improving their evaluability. This heightened the sensitivity to probability variations.

3. General Discussion

3.1 Summary of Results

Our study systematically demonstrates the common existence of opportunity cost neglect (OCN) in preventive judgments and decisions. Experiment 1 uses standard methods to show the existence of OCN and settle it down in the domain of sick leave loss. People tend to overlook sick leave losses from illnesses and will systematically increase their inclination to consider it when prompted to think about it. Experiments 3-7 systematically showcases the four important behavioral patterns associated with OCN: insufficient risk perception, duration neglect, probability insensitivity, and the lack of positive correlation between income and WTP. These biases are prevalent and typically welfare-decreasing, and are more severe when the OC is less salient and less evaluable.

Simultaneously, our main treatment, AUM, consistently showcases high effectiveness in mitigating OCN, presenting it as an innovative intervention that encourages participants to actively quantify the economic implications of illnesses, acting as a remedy for these biases. Experiment 2 shows that AUM leads to a higher-quality thinking about OC than just mentioning

sick leave loss qualitatively. In Experiments 3 and 4, we experimentally assessed the proposition that AUM amplifies risk perception. By emphasizing the salience and evaluability of the economic impacts of diseases, AUM counters the biases like opportunity cost neglect, enhancing individuals' risk awareness and their willingness-to-pay (WTP) for preventive actions. Experiments 5-7 provide additional evidence for AUM's benefits from the mechanism of evaluability. Utilizing economic loss as a reference point and scale, AUM heightens the clarity of disease-related duration and probability data, countering biases such as duration neglect and probability insensitivity. This approach ensures individuals more effectively integrate this information into their health-related decisions. Our results demonstrate significant consistency and effect magnitude, providing a firm basis for exploring both its theoretical insights and practical applications.

3.2 Strengths and Implications

The key strength of this paper is that we systematically justify the prevalence of OCN in preventive health judgments, pins it down in the domain of sick leave loss, and holistically show its behavioral and economic impacts. This is a meaningful extension of standard health demand models such as the Grossmann Model to the behavioral battleground and serves as an effective tool in explaining the "low-hanging fruit" paradox. By summing up the findings of all our experiments, we can clearly see the necessity of promoting people's understanding in sick leave OC in engaging better preventive decisions and behaviors.

Another major innovation is to use financial loss calculation tasks to enlighten monetary thinking, achieving two objectives simultaneously. On the one hand, it increases the salience of economic losses in people's perception, addressing the issue of limited attention and opportunity cost neglect. On the other, it interprets the abstract and emotion-rich health losses into quantifiable monetary values, mitigating the evaluability problem. To our knowledge, this paper is the first to systematically categorize health decision biases into these two dimensions and propose interventions that effectively offer a solution to both biases simultaneously.

The next notable strength of our study is its extensive scale and resilience to experimental setups. We gathered health evaluations from 7 experiments and nearly 6,000 participants, examining their decision-making behaviors concerning various diseases. For lab-based research, this scale is substantial, allowing us to scrutinize the primary experimental effect with strong statistical power and stable effect size across diverse demographics, socioeconomic statuses (such as the availability of paid sick leave and whether living paycheck to paycheck), and individual decision-making characteristics (such as numeracy and risk preferences). This approach enables a thorough examination of AUM's relatively unanimous impact for different groups of individuals. Our findings, which remain consistent across different model specifications, bolster our confidence in AUM's potential real-world applicability.

Additionally, this paper's practical orientation provides practical insights for future implementation. We provide recommendations for two scenarios. The first scenario involves the most common web platform disease descriptions. Using COVID-19 as an illustration, health communicators could emphasize the potential economic impacts of diseases, such as Long COVID, whose major symptom is fatigue that may lead to months of inability to work. Without extended paid sick leave, this could translate to significant wage loss. Health communicators

could engage users with a prompt, suggesting, "You can input your monthly income figure to estimate the financial loss you could potentially avoid, on average, if you evade long COVID." The crux of this strategy is to swiftly make website visitors aware of the potential economic implications of the illness. This feature should be prominently positioned on the website, ensuring users can easily access and utilize it. (Evidently, the UM approach might not be as apt, given that websites cannot pre-access users' income data.) The second context pertains to direct medical communication, such as interactions between insurance companies and clients, doctor-patient conversations, or caregivers guiding at-risk individuals. Given the substantial difficulties of casting field experiments with a novel nudge, this paper did not undertake in-depth empirical tests for this context. Nonetheless, we offer actionable insights grounded in our findings and theoretical framework. AUM can be further customized if the communicator and the decision-maker are in a closer relationship. The communicator can guide the decision-maker's calculations, while also prompting deeper reflection on the economic implications of illnesses, including potential medical expenses and wage losses, and their potential size compared to the cost of prevention. This thoughtful engagement not only promotes salience and evaluability, but also stimulates System II thinking, empowering the other party to make well-informed decisions aligned with their best interests.

Lastly, it is particularly important to note that our consistent use of online experiments does not strongly compromise external validity. In a digital world, many individuals retrieve disease prevention information from reputable online platforms, such as the websites of the CDC and Mayo Clinic. Users often browse these sites without deep reflection. Many prevention decisions are thus made after this brief information acquisition.

Therefore, internet-based 'System I' decisions may play an important role in real life. The online experiments regarding the AUM in this paper are a good exemplification that preliminarily explores the potential of AUM as an applicable intervention in online health and policy communication.

3.3 Limitations and Future Perspectives

This study has several noticeable limitations. Given constraints related to paper length and research costs, it's challenging to exhaustively address all facets in one paper, prompting this section to outline future prospects for AUM interventions as well.

A primary limitation is that our experiments are mostly hypothetical and focusing on deductive processes rather than real health behaviors. Although hypothetical and conceptual scenarios are frequently used in the contingent evaluation literature, its effectiveness in online experiments and preventive decisions is still pending solid proof. Thus, the external validity of these experiments may still open to further investigation. This promotes us to conduct field experiments to demonstrate the real-world prevalence of OCN and impacts of AUM in the future. Another way is to construct incentivized decision flow lab experiments that mimic real-world disease prevention and sick leave losses among university students.

An additional limitation pertains to the variability in income, financial stability, and sick leave statuses, along with the ensuing practical challenges. While our findings indicate that factors like income and economic resilience primarily act as covariates without significant

interaction with our treatments, this could be attributed to an inadequate sample size preventing a comprehensive exploration of all potential interactions. Despite its good emulation of real-world scenarios, the current version of AUM is still largely conceptual and does not fully incorporate many details in preventive decision-making. For example, the detailed breakdown doesn't factor in aspects like paid sick leave status or anticipated medical expenses, given the constraints of online survey methodologies.

This drives our ambition to refine AUM, tailoring it more personally and aligning it closer to real-world decision-making scenarios in the future. Specifically, for economically disadvantaged individuals or those living paycheck to paycheck, there's potential for enhancement. A structured breakdown of their risk profile could foster a deeper understanding and heightened preventive awareness.

A potential critique is that AUM, designed as a cognitive tool to amplify risk awareness, could have adverse welfare consequences in specific contexts for particular individuals. While welfare considerations in Experiments 3-6 indicate promising potential for welfare benefits and Experiment 7 implies a guaranteed increase (because the insensitivity in Experiment 7 is not rationalizable), the outcomes aren't uniformly positive across all participants and scenarios. In the future, more comprehensive and stringent welfare evaluations will be crucial.

4. Conclusion

This paper formally introduces the notion of opportunity cost neglect to the health economics literature. It may lead to three behavioral biases about insufficient risk perception, duration neglect and probability insensitivity, and we justify their prevalence using seven experiments from US online users. Simultaneously, we demonstrate that these biases can be significantly mitigated by prompting people to actively calculate dollar amount of the opportunity costs from sick leaves.

Following [Grossmann \(1972\)](#), we emphasize the importance of opportunity costs about sick leave and missed leisure in preventive health decisions and made propositions why they may be considered insufficiently: low salience and low evaluability. Because opportunity costs are usually indirect and less conspicuous to decision-makers, people may have inadequate attention to them and fail to include them when making health decisions. Moreover, when these costs are not quantified by monetized amounts, people may encounter difficulties in mapping them to a clear evaluation of the loss. These two cognitive limitations determine the prevalence of OCN in preventive decisions. Thus, we designed an intervention that prompts users to think of money and therefore improves their consideration in opportunity costs.

First, there are two important empirical questions coming along: to what extent people neglect opportunity costs, and whether sick leave or leisure loss dominates. Our first two experiments consistently show that opportunity costs, especially sick leave costs are significantly neglected, as increasing the salience and evaluability of these costs can largely promote people's consideration. In contrast, leisure losses seem to be marginal. Moreover, increasing salience and evaluability simultaneously (by AUM) works better than only

increasing the salience (reminding people of salary loss).

We explore more detailed mechanisms and solutions to OCN by five extra experiments. Experiments 3-4 systematically show the insufficient perception of OC in environments without talking money. Then, we show that both salience and evaluability matter for risk perception level. Mentioning unpaid leave (salary loss) and the computation process can increase risk perception. On the contrary, the process of “active calculation” seems to have limited marginal impact.

Experiments 5-7 focus on the numerical insensitivity issues regarding time duration (the timespan an illness lasts) and probability (effectiveness of preventive measure). With both between-subject (single evaluation) and within-subject (joint evaluation) studies, we demonstrate that OCN and numerical insensitivity problems frequently happen in single evaluation, consistent with our theoretical predictions. AUM can largely mitigate these problems. In these cases, the welfare impact of OCN and the effectiveness of AUM is well supported, because rational decision-makers will never view a 30% and 60% effective vaccine as the same. In within-subject cases, although AUM still enlarges numerical sensitivity, the welfare implications should be further discussed.

The existence of OCN, its subsequent behavioral implications, and the effectiveness of talking money seem to be robust in preventive judgment processes. If future research (especially incentivized lab experiments and field experiments) corroborates our findings, it could suggest that emphasizing the less salient opportunity costs of diseases should be an effective tool for policymakers and medical practitioners to promote healthier behavior and overcome the “low-hanging fruit” paradox.

In terms of clearer policy implications, our general results indicate that people with OCN can be a valuable target group for effective public health communication campaigns to promote preventive behaviors. Including hints on opportunity costs (especially sick leaves) to essential health communication processes, in addition to nudging people to seriously consider the financial loss from sick leaves, is a potentially effective policy. Specifically, online health communication and education platforms can include a dialog box that allows the visitor to anonymously input their salary status and immediately calculate the OC of sickness. Our findings suggest that this intervention is likely to help mitigate the “low-hanging fruit” paradox without over-enhancing the risk perception and prevention behaviors. It is thus in accordance with the ethics of nudging ([Blumenthal-Barby & Burroughs, 2012](#)) and libertarian paternalism ([Sunstein, 2014](#)).

Finally, our study is a first attempt to connect OCN – a popular behavioral bias – to health economics and preventive health from a serious experimental perspective. Although our experimental analysis is solely based on hypothetical decisions, we believe it is a treasure box to study the relevance of missing OC awareness in health judgments and design relevant behavioral interventions. In particular, future research should dig deeper into the external validity of OCN in health research and generalize it into more real-world contexts, different diseases and different countries.

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