Wait and See or Take Preventive Action?

On Sequential Decision Making in a Cost-Loss Game

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Abstract

Problem Definition: People frequently face sequential decision problems. For example, functioning objects may degrade over time, increasing the probability of failure. Preventive actions can halt this degradation, but come at a cost. We examine how individuals decide when to take such preventive actions. **Methodology/Results:** We analytically derive an optimal threshold policy indicating the ideal timing for preventive action in a degradation process with an increasing likelihood of failure. We conducted a laboratory experiment using two treatment variables: (1) the size of the potential loss, theoretically determining the threshold, and (2) the speed of degradation, theoretically irrelevant to the threshold. Experimental results reveal that participants show limited sensitivity to the potential loss size while substantially responding to the degradation speed. We identify a convex relationship between the decision stages and participant's subjective threshold; this explains our primary results. Furthermore, we conclude that anticipated regret, loss aversion, and probability weighting collectively drive this convex relationship. Three further experiments confirm these findings: An experiment with experts, one with deterministic degradation, and one with a constant failure probability. **Managerial Implications:** Our findings show that individuals tend to act too early when facing small losses and too late when losses are large, suggesting that they incorporate in their decision the number of previously made decisions. Practically, managers can leverage the observed stage effect by adjusting decision frequencies in contexts such as machine maintenance, thereby enhancing overall efficiency.

Keywords: sequential decisions, preventive action, behavioral bias, experiments, maintenance decisions

1 Introduction

Sequential decisions are pervasive in both professional and personal contexts. A key example is the decision to take preventive action, which is essential for avoiding potential losses. Such actions span large-scale societal efforts, including reducing carbon emissions and transitioning to renewable energy, to individual actions such as car maintenance, vaccinations, and descaling espresso machines.

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In the manufacturing context, actions to prevent machine breakdown are high-value-added activities. Siemens (2022) reports that unplanned downtime at Fortune Global 500 companies cost 11% of their annual turnover in 2022, amounting to nearly $1.5 trillion. ABB (2023) surveys 3,215 plant maintenance leaders and finds that machine breakdowns cost the plants $125,000 per hour. Deloitte Analytics Institute (2017) estimates that condition-based maintenance increases productivity by 25%, reduces breakdowns by 70%, and lowers maintenance costs by 25%. Condition-based maintenance uses direct real-time machine condition monitoring to conduct preventive maintenance just before failure is imminent (Mobley 2002). In the healthcare context, actions to prevent diseases are vital activities that can save lives. For example, women carrying the BRCA gene are at a higher risk of breast cancer. They can take preventive actions by using medicines and undergoing surgery to reduce the breast cancer risk (American Cancer Society 2021).

These preventive actions share three common features. First, the probability of potential damage can be estimated. For example, the probability of a machine breakdown can be predicted by analyzing historical data, monitoring temperatures, and measuring vibration amplitudes (Arts and Basten 2018). Similarly, the risk of breast cancer is assessed through gene mutation tests, patient age, and other diagnostic and demographic data (Sakorafas et al. 2002). Second, this probability increases stochastically over time, leading to a dynamic process known as a *degradation process*. This process is well-known in various fields, including machine maintenance, disease progression, and climate change. Third, a preventive action terminates the degradation process. For example, preventive maintenance may mean that a system is replaced with a new one (Caballé et al. 2015).

The timing of taking action is crucial. If the action is taken too early, a preventive cost is paid unnecessarily. In machine maintenance, this is called over-maintenance and it wastes company resources (Öhman et al. 2015, Cavalier and Knapp 1996). In preventive healthcare, unnecessary care (Carroll 2017) and over-treatment (Ooi 2020) have attracted a great deal of attention from practitioners and researchers in recent years. By contrast, if people wait too long, they could incur a large loss such as system failure, illness, or even death.

Humans may exhibit a variety of behaviors when faced with risk. Prospect theory (Tversky and Kahneman 1992) suggests that individuals tend to be risk-averse or loss-averse and engage in probability weighting. In a dynamic environment, risky choices may exhibit path dependence, as shown by Post et al. (2008) in the context of the television game show *Deal or No Deal*: they find that risk aversion decreases over time, influenced by outcomes observed in earlier stages. Moreover, in Baumann et al. (2020)'s optimal stopping experiment, the decisions align with a linear threshold model: the threshold that individuals use to decide when to stop searching increases linearly over time.

Thus, the goal of this study is to examine human behavior in taking preventive actions within a dynamic process. We begin with an analytical model, in which time is discretized into a sequence of stages, the total number of which is unknown a priori. An object faces a failure risk of which probability increases stochastically over stages. The owner receives a benefit at each stage until the process ends, due to either a failure or a preventive action. At each stage, the owner decides whether to take preventive action, at a cost, or to wait. Waiting allows benefits to continue if no failure occurs, but it also risks termination upon failure at a loss. Each stage's decision thus resembles the cost-loss game framework of Roulston and Smith (2004) and Bolton and Katok (2018), in which the trade-off is between paying either a cost to avoid potential failure or risking failure by doing nothing. We show that under an optimal policy, the owner takes preventive action once the failure probability exceeds a critical threshold, consistent with the threshold policy found by Taylor (1975). This threshold depends jointly on the prevention cost, the size of the loss, and the per-stage benefit.

We conduct a laboratory experiment in which the object is framed as a machine and the damage as its breakdown. The failure probability is observable at each stage, representing a form of condition-based maintenance (see, e.g., McCall 1965, Monahan 1982, Feiler et al. 2013). Subjects make decisions over an a priori unknown number of stages in which the failure probability increases as the process unfolds. At each stage, they observe the current failure probability and decide either to take preventive action or to wait. If they wait and no failure occurs, the process continues to the next stage. Payoffs equal the accumulated stage benefits minus either the cost of preventive action or the loss from failure, depending on how the process ends.

The experiment consists of 20 rounds, such that each subject makes decisions in 20 independent sequences of stages. We vary two treatment variables. The first is the size of the loss incurred upon failure, which takes three levels. We refer to these as the *loss-variant* treatments, where a larger loss decreases the optimal threshold for taking preventive action. The second is the maximum increment in failure probability from one stage to the next, referred to as the maximum degradation speed, which also varies across three levels. We refer to these as the *speed-variant* treatments, where the optimal threshold remains unchanged. All treatments follow a between-subjects design.

We derive two key empirical findings from our experiment. First, the effect of a larger loss on inducing earlier preventive action is significantly weaker than theoretically predicted. Second, the degradation speed exerts a strong influence on preventive decisions, whereas theory suggests no such impact. Analyses reveal that subjects' decisions are shaped not only by the failure probability but also by the number of stages. In particular, the critical probability that triggers preventive action is not a constant threshold, as theory predicts. Instead, it is convex in the stages with a clear decrease over the initial stages. This pattern helps explain the two key findings above. It echoes the stage effect identified by Baumann et al. (2020) in their optimal stopping game, although in their case, the threshold used to decide when to stop searching increases linearly over time.

We consider four behavioral models commonly used to explain human decision-making under risk. The first three models, risk aversion, loss aversion, and probability weighting, are derived from prospect theory (Tversky and Kahneman 1992). The fourth model, anticipated regret, is based on Bell (1982). Our results indicate that anticipated regret is the primary driver of behavior, while loss aversion and probability weighting offer complementary explanatory power. These findings suggest that multiple behavioral factors jointly shape decisions and help account for the observed nonlinear stage effect.

We conduct three additional experiments to test the robustness of our findings. In the first, we fix the incremental increase in failure probability across stages and make this information explicit to subjects. The results confirm the nonlinear stage effect and the associated behavioral explanations. In the second experiment, we fix the failure probability at 0.1 across all stages to examine the stage effect. In this simplified setting, participants increasingly take preventive actions after several stages, again confirming the stage effect. Finally, we replicate the original experiment with workshop participants who are researchers and practitioners active in condition-based maintenance, and we observe behavioral patterns closely resembling those in the lab experiment.

Our findings have broad practical relevance for dynamic decision making. For instance, technicians may carry out maintenance too early when the potential loss is small, or too late when the potential loss is large. Managers can address this bias by adjusting the frequency of decision making, thereby correcting premature or delayed maintenance and improving efficiency. Similar dynamics arise in other domains: for example, increasing the frequency of health checkups for life-threatening conditions can encourage more timely and effective preventive decisions.

2 Relevant Literature

To our knowledge, this paper is the first to study maintenance decision-making in a laboratory setting. We focus on condition-based maintenance (CBM) which is a preventive maintenance strategy in which maintenance decisions are based on the machine's condition, assessed through the analysis of continuous monitoring data (Jardine et al. 2006). CBM is an important topic in the fields of reliability engineering and operations research. In recent years, this topic has become increasingly popular as the availability of machine data and advanced data analysis methods has enabled companies to adopt CBM (e.g., Keizer et al. 2017, De Jonge and Scarf 2020, Akkermans et al. 2024). The current CBM literature focuses on maintenance strategies (Do et al. 2015), optimal policies (Sanoubar et al. 2023, Grall et al. 2002, Chen and Trivedi 2005), failure diagnostic techniques (Barajas and Srinivasa 2008), information systems (Bousdekis et al. 2015), and so on. Some studies also concentrate on developing decision support systems (Parvizsedghy et al. 2015, Yam et al. 2001, Jamil et al. 2013) to assist human decision-making in CBM contexts. Despite the central role that humans play in many maintenance decisions, research on human decision-making in maintenance remains limited. This study provides initial insights into behavioral biases that affect decision-making in the context of condition-based maintenance. These behavioral findings can be incorporated into CBM models to develop maintenance policies that more accurately reflect and accommodate human decision-making patterns.

Our study also contributes to the literature on sequential decision making under uncertainty, especially for the optimal stopping problem and the balloon analogue risk task (BART). In the optimal stopping problem, individuals make sequential decisions regarding a series of random rewards, choosing either to stop and collect the current reward or to continue in hopes of obtaining a better reward in the future (Siegmund 1967). The secretary and marriage problems are two well-known optimal stopping problems (Ferguson 1989). Seale and Rapoport (2000) conducted a lab experiment on the secretary problem with an unknown number of applicants and found that decision makers stopped too early. Lee (2006) conducted a classic optimal stopping experiment in which decision makers chose the maximum number from a list of sequentially presented numbers. They found that a position-dependent threshold well explained the behavior. In Baumann et al. (2020)'s optimal stopping game, when to stop searching linearly increases over time. Post et al. (2008) analyze empirical data from the *Deal or No Deal* TV game show, where contestants sequentially decided whether to accept a bank offer or to reject it in favor of getting a better offer in the future. They found evidence of path dependence influencing contestants' decisions. Our dynamic preventive decision context differs fundamentally from such optimal stopping games in two ways. First, optimal stopping models typically assume a finite horizon, making the number of stages directly relevant to the optimal policy. In contrast, our preventive decision scenario assumes an indefinite horizon, rendering the stage number irrelevant to the optimal threshold. Second, preventive decision-making in our study occurs within a degradation process in which failure probabilities are explicitly revealed to decision-makers, whereas typical optimal stopping models do not involve such information revelation.

In the BART, a participant clicks on a pump to inflate a balloon. Each pump adds a monetary increment to a temporary bank. If the participant stops pumping, all the money in the temporary bank is collected. If pumping causes the balloon to explode, all the money is lost. Lejuez et al. (2002) designed this game to measure risk-taking behavior, incorporating a degradation process. However, our game differs from the BART in two key ways. First, the loss amount in our game is fixed, whereas in the BART, losses increase with each additional balloon inflation, where all money in the temporary bank is lost if the balloon explodes. Second, in our game, the failure probability is given to the participants, while it remains unknown in the BART. Because of these differences, existing dynamic game studies like the BART do not show how people make preventive decisions. The behavioral evidence from our study gives new insight into how people make decisions in dynamic settings.

Our findings also echo results from research on queuing behavior. First, people often rely on information that is not relevant according to standard theory. For example, Luo et al. (2025) find that when subjects wait longer in queuing tasks, they demand lower pay per unit of time—contrary to the theory that the cost of waiting should be constant. Similarly, Estrada Rodriguez et al. (2024) show that the scheduling policy, rather than the waiting time itself, affects lying behavior in queuing systems. Second, consistent with our nonlinear stage effect, Kumar et al. (1997) find a non-monotonic pattern: when customers expect long service times, their satisfaction drops early on but then increases towards the end of the wait. Third, when faced with complex and changing information, people may simplify, ignore, or overreact to important details. For instance, Hathaway et al. (2023) find that cognitive limits and bounded rationality can lead people to overreact to transfer costs in queuing systems.

Our study is closely related to other theoretical and experimental research on sequential decision-making under uncertainty. However, by focusing on preventive actions, we address a practically important type of behavior that has been largely overlooked in the literature.

3 Analytical Model

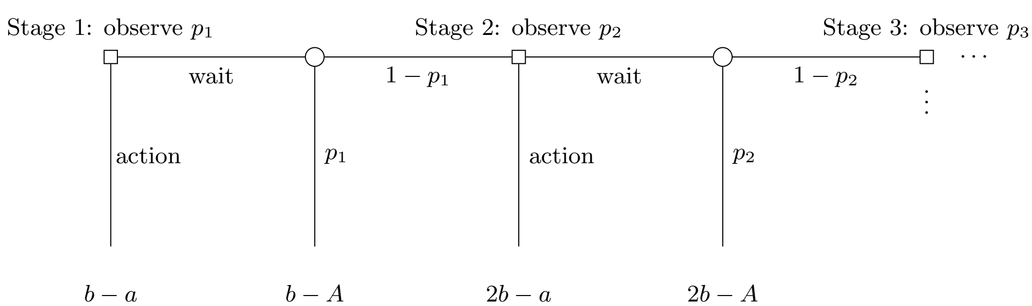
We present a mathematical model of preventive decisions in a degradation process and analytically show that a threshold policy is optimal. The optimal threshold decreases with the size of the loss but is independent of the degradation speed. In Section 4, we use these analytical results for risk-neutral decision makers as the foundation for our experimental design and hypotheses.

3.1 Basic Setting

We discretize time into stages, indexed by $s \in \{1, 2, \ldots, \infty\}$. An owner (referred to hereinafter as *she*) has an object that brings her a benefit of $b > 0$ for usage in each stage. However, the object is subject to failure, with its probability increasing over stages. The probability of failure at each stage s, denoted as p_s, is $p_s = \min\{p_{s-1} + d_s, 1\}$, with $p_0 = 0$ and d_s randomly drawn from a uniform distribution in the range $(0, m]$, with $m > 0$. We refer to this dynamic process as the *degradation process.* We focus on a stochastic degradation process because it reflects the inherent uncertainty of future states, as commonly encountered in real-life degradation scenarios. For instance, technicians are often unable to precisely predict the condition of a machine for the next inspection period. The upper bound of the increment of the failure probability, m, indicates the *maximum degradation speed* (max degradation). The process is terminated either by a failure or by the owner's preventive action. If terminated by a failure, the owner suffers a *loss* $A > 0$. If terminated by a preventive action, the owner pays a preventive *cost* a, with $A > a > 0$, and typically $A \gg a$.

In Figure 1, we illustrate the owner's decisions and relevant payoffs in the degradation process. In stage 1, she observes the failure probability p_1 and chooses between two options: *action*, meaning she takes preventive action and pays the preventive cost a, or *wait*, meaning no preventive action is taken. Taking action terminates the process immediately and yields a payoff of $b - a$. Choosing to wait leads to two possible outcomes: with probability p_1 a failure occurs, terminating the process and resulting in a payoff of $b - A$; with probability $1 - p_1$ nothing happens, and the owner proceeds to stage 2. There, she observes the new failure probability p_2 and faces the same decision between action and wait (with resulting payoffs of $2b - a$ and $2b - A$ with probability p_2, respectively). The process continues in this fashion until it is terminated either by failure or by preventive action. Note that as $p_s = 1$ for some finite stage s, the process terminates due to failure with certainty after a finite number of stages if no preventive action is taken.

Figure 1: An Extensive Form Representation of the Owner's Decisions in a Dynamic Process



3.2 Optimal policy

Here, we provide the intuition behind the result. To do so, we make a simplifying assumption: the owner acts myopically, choosing between taking action now or postponing it to the next stage. In Online Appendix A, we show that this myopic decision rule leads to the overall optimal policy, a result consistent with Taylor (1975). It is worth noting that in other dynamic game settings, such as that of Kagan et al. (2025), myopic behavior does not align with the fully rational model.

Taking action now leads to a certain payoff $sb - a$, while waiting and taking action at the next stage leads to an expected payoff $p_s(sb - A) + (1 - p_s)(sb + b - a)$. Removing the common term sb, we find that it is optimal to take action now if $-a > -p_s A + (1 - p_s)(b - a)$ and to wait if the inequality is reversed. The left-hand side term, $-a$, can be interpreted as the cost (or negative benefit) of taking action now. The right-hand side term, $-p_s A + (1 - p_s)(b - a)$ can be interpreted as the cost of taking action at the next stage and is monotonically decreasing in p_s if $A + b - a > 0$. This condition always holds in our setting since $A > a$ and $b > 0$. Because the failure probability p_s increases over stages in the degradation process, there exists a threshold p^* such that for $p_s < p^*$, waiting dominates, while for $p_s > p^*$, immediate action is optimal.

We thus obtain Theorem 1 indicating the optimal threshold policy.

Theorem 1. *There exists an optimal probability threshold $p^* = \frac{b}{A+b-a}$ such that at any stage s it is optimal to (a) wait if $p_s < p^*$, (b) take action if $p_s > p^*$, and (c) choose either one of the two options if $p_s = p^*$.*

4 Experiment Design and Hypotheses

The baseline treatment, referred to as *F4*, uses the parameters $a = 1$, $b = 1$, $A = 4$, and $m = 0.05$. We have two treatment variables: the size of the loss, A, which increases to 6 and 10 to obtain treatments *F6* and *F10*, respectively, and the maximum degradation speed, m, which increases to 0.10 and 0.15 to obtain treatments *F4-10* and *F4-15*, respectively. We refer to treatments *F4*, *F6*, and *F10* as the *loss-variant* treatments in which the optimal threshold p^* varies across treatments, and we refer to *F4*, *F4-10*, and *F4-15* as the *speed-variant* treatments in which the optimal threshold is invariant. Table 1 summarizes the setup of the experiment.

Table 1: Treatments with Parameters and Number of subjects

Treatment	Loss A	Max degradation m	Optimal threshold p^*	subjects N
F10	10	0.05	0.10	35
F6	6	0.05	0.17	37
F4	4	0.05	0.25	36
F4-10	4	0.10	0.25	36
F4-15	4	0.15	0.25	36

We recruited 180 subjects via Ancademy (`https://www.ancademy.org/`). We programmed the experiment software using z-Tree (Fischbacher 2007). The subjects were undergraduate and graduate students studying at a public university in China. Including a show-up fee they earned RMB 50.98 on average for a one-hour experiment. The experiment currency was labeled by real-life currency, and therefore the exchange rate was 1. Subjects were allowed to take part in one treatment only.

The experiment consists of 20 rounds. At the beginning of each round, the subjects were informed that they were entitled to a brand-new fictitious machine, in a condition that deteriorates over the stages (Online Appendix B shows the instructions given for one treatment). At each stage s, after being informed of the failure probability p_s, the subjects decided whether or not to pay a cost $a = 1$ to prevent the failure. Paying the cost would immediately end the round. By choosing to wait, a failure that ends the round might occur with a probability p_s. If no failure occurred, stage $s + 1$ started. We refer to the stage in which a round ends as the *end-stage*, denoted by $\bar{s}$. Given that in the experiment $a = b = 1$, subjects either earned payment $\bar{s} - 1$ if the round ended by preventive action or earned payment $\bar{s} - A$ if it ended by failure. A review page appeared when each round ended, summarizing the decision results to the current and previous rounds. The subjects did not interact with others, making decisions individually.

The degradation process, consisting of a series of failure probabilities and corresponding failure or no-failure outcomes, is pre-generated independently for each subject and each round. These pre-generated processes allow for paired comparisons among the loss-variant treatments and are also used to calculate theoretical predictions based on the optimal threshold. In these pre-generated processes, the longest sequence until failure spans 25 stages. In the experiment, a few subjects reached stage 21 but did not progress further.

We construct two directional predictions based on the optimal threshold policy stated in Theorem 1.

Hypothesis 1. *In the loss-variant treatments, a larger potential loss leads to taking preventive action at a lower failure probability.*

Hypothesis 2. *In the speed-variant treatments, a larger maximum degradation speed does not affect the failure probability at which preventive action is taken.*

As we cannot directly observe at which failure probability a decision-maker is willing to take action, we look at three measures. Let $\bar{s}$ denote the final stage in which a subject either takes preventive action or experiences failure in a given round. The corresponding failure probability at that stage, $p_{\bar{s}}$, is classified as (a) the *action-end probability* if the subject takes action, and (b) the *failure-end probability* if the process ends in failure. In the case of preventive action, we additionally compute (c) the *implied threshold*, defined as $(p_{\bar{s}-1} + p_{\bar{s}})/2$, i.e., the average of the action-end probability and the failure probability observed in the preceding stage. The rationale is that the true failure probability at which the subject decided to act must lie somewhere between these two values. With no further information, the midpoint serves as the best estimate.

5 Experiment Results

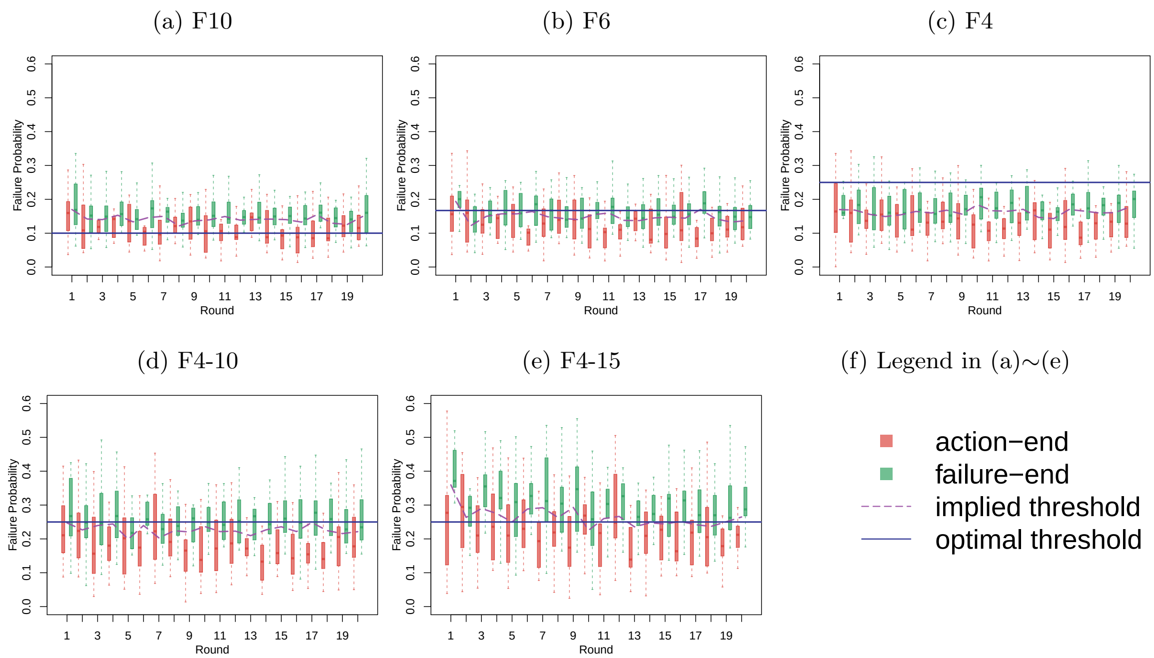
We first analyze the impact of the size of the loss A and the maximum degradation speed m on taking preventive action. These results are used to test the hypotheses formulated in Section 4. Second, we conduct a linear Probit regression on subjects' action decisions, using failure probability, round, and stage as independent variables to provide additional insights.

5.1 The Impact of A and m on preventive actions

Figure 2 illustrates the decision patterns across 20 rounds in the five treatments. The red box plots present the action-end probabilities, while the green box plots depict the failure-end probabilities.

The dashed line shows the average implied threshold across subjects, and the blue straight line indicates the optimal threshold for each treatment. In the loss-variant treatments (see panels (a)–(c)), the optimal threshold increases as the loss decreases, while the implied threshold remains fairly stable, in the range of 0.1–0.2. This suggests that the size of the loss has only a limited influence on preventive decisions. In the speed-variant treatments (see panels (c)–(e)), the optimal threshold is constant at 0.25, yet the implied threshold rises as the degradation speed increases.

Figure 2: Decisions and the Optimal Thresholds in Treatments



Rigorous comparisons between the optimal and implied thresholds are summarized in Table 2. The theoretical predictions (TP) are derived by applying the optimal threshold to the pre-generated degradation processes used in the experiment. Based on the resulting simulated decisions, we compute all relevant performance indicators.

The table reveals differences between the experimental data and TP in the F10, F4, and F4-15 treatments. Specifically, the higher action-end and failure-end probabilities in the F10 and F4-15 treatments suggest that subjects tend to act too late relative to the TP. In contrast, the lower action-end and failure-end probabilities in the F4 treatment indicate that subjects act too early. In the F6 and F4-10 treatments, experimental behavior is mostly aligned with theoretical predictions.

Table 2: Descriptive Statistics of the Subjects' Performance Across Treatments and the Corresponding Theoretical Predictions

	F10	F6	F4	F4-10	F4-15
	Loss-variant treatments				
			Speed-variant treatments		
Payoff	**1.0529*****	**2.6446**	**3.6194***	**1.8986**	**0.9861*****
	(0.8836)	(0.7806)	(0.8207)	(0.5319)	(0.4625)
TP	*1.6186*	*2.8122*	*3.9694*	*2.0944*	*1.2681*
	(0.9849)	(0.6973)	(0.6979)	(0.5930)	(0.4597)
End-stage	**5.6914*****	**5.8946**	**6.2278*****	**4.3861**	**3.5611****
	(0.9910)	(1.0854)	(1.1087)	(0.6270)	(0.4747)
TP	*4.2771*	*5.9676*	*7.1361*	*4.4444*	*3.3222*
	(0.2545)	(0.3803)	(0.5065)	(0.3033)	(0.2503)
Failure rate	**0.4043*****	**0.4500**	**0.5389*****	**0.4958**	**0.5250*****
	(0.1437)	(0.1740)	(0.1512)	(0.1601)	(0.1650)
TP	*0.1843*	*0.4311*	*0.7222*	*0.4500*	*0.3514*
	(0.1069)	(0.0916)	(0.0960)	(0.1171)	(0.0989)
Action-end probability	**0.1638*****	**0.1730**	**0.1872*****	**0.2710***	**0.3190***
	(0.0424)	(0.0434)	(0.0433)	(0.0550)	(0.0637)
TP	*0.1156*	*0.1835*	*0.2655*	*0.2825*	*0.2963*
	(0.0069)	(0.0032)	(0.0055)	(0.0073)	(0.0074)
Failure-end probability	**0.1190*****	**0.1241*****	**0.1323****	**0.1800*****	**0.2204*****
	(0.0264)	(0.0251)	(0.0290)	(0.0349)	(0.0449)
TP	*0.0684*	*0.1062*	*0.1458*	*0.1567*	*0.1603*
	(0.0164)	(0.0147)	(0.0136)	(0.0188)	(0.0196)
Implied Threshold	**0.1494*****	**0.1578**	**0.1729*****	**0.2392**	**0.2743****
	(0.0426)	(0.0425)	(0.0431)	(0.0552)	(0.0613)
TP	*0.1007*	*0.1663*	*0.2489*	*0.2481*	*0.2448*
	(0.0071)	(0.0026)	(0.0047)	(0.0065)	(0.0077)

Note, standard deviations across subjects are in parentheses.
TP denotes the theoretical prediction under risk neutrality.
According to the Wilcoxon rank sum test, the experimental data are different from the *TP* at the * 10%, ** 5%, or *** 1% significance level.

To test Hypothesis 1, we compare the action-end probability across the loss-variant treatments using Wilcoxon rank sum tests. The probability decreases slightly from 0.1872 to 0.1730 to 0.1638 as the loss of A increases from 4 to 6 to 10. The pairwise differences between F4 and F6 ($p = 0.1437$) and between F6 and F10 ($p = 0.2324$) are not statistically significant. The difference between F4 and F10 is statistically significant ($p = 0.0095$), yet the effect size of 0.0234 is much smaller than the theoretical prediction of 0.1499. A similar pattern emerges for the failure-end probability and the implied threshold. Although the implied threshold difference between F4 and F10 is statistically

Table 3: Linear Regression on Action-end probability, Failure-end Probability, and implied Threshold in the Loss-variant Treatments

	Action-end probability		Failure-end probability		Implied threshold	
	Data	*TP*	Data	*TP*	Data	*TP*
Constant	0.1977***	0.3422***	0.1441***	0.1953***	0.1831***	0.3242***
	(0.0118)	(0.0044)	(0.0076)	(0.0048)	(0.0117)	(0.0046)
A	-0.0036***	-0.0233***	-0.0023***	-0.0133***	-0.0036***	-0.0230***
	(0.0017)	(0.0006)	(0.0011)	(0.0008)	(0.0016)	(0.0006)
LogLik	-1986.69	-2692.30	-1521.85	-1503.63	-2023.18	-2729.63
Observations	1156	1192	1004	968	1156	1192

Across all measures, the coefficient of A in the data is significantly different from that in *TP* ($p < 0.01$, Welch's t-tests).
* 10%, ** 5%, or *** 1% significance level.

significant (0.0235, $p = 0.0109$), it remains far below the theoretically predicted difference of 0.1482.

Table 3 reports regressions on the effect of the loss size on the action-end probability, failure-end probability, and implied threshold. Again, *TP* denotes the theoretical predictions. Since A is significant in all models, Hypothesis 1 is supported: the size of the loss does affect preventive actions. However, the effect is far weaker in the data than in theory. For instance, the coefficient on action-end probability is less than one-fifth of the TP estimate (-0.0036 vs. -0.0233). Welch's modified two-sample t-tests confirm that these differences are statistically significant ($p < 0.01$). Overall, subjects' preventive actions are much less sensitive to the loss size than theory predicts. Therefore, we summarize this finding in Result 1.

Result 1. *In the loss-variant treatments, subjects take preventive actions that are not sufficiently responsive to the size of the loss.*

For the speed-variant treatments, we first compare the implied threshold, which increases from 0.1729 to 0.2392 to 0.2743 as the maximum degradation speed m increases from 0.05 to 0.10 to 0.15. The difference between F4 and F4-10 is 0.0663 and is significant at the 1% level ($p < 0.01$), while in the *TP* the corresponding difference is not significant ($p = 0.6322$). The difference between F4-10 and F4-15 is 0.0351 ($p = 0.0189$), whereas in the *TP*, it is -0.0033 ($p = 0.0507$). These findings indicate that the implied threshold rises with m, in contrast to the theoretical prediction. The action-end and failure-end probabilities follow the same pattern, showing sharp increases with

Table 4: Linear Regression on Action-end Probability, Failure-end Probability, and Implied Threshold in the Speed-variant Treatments

	Action-end probability		Failure-end probability		Implied threshold	
	Data	*TP*	Data	*TP*	Data	*TP*
Constant	0.1212^{***}	0.2511^{***}	0.0936^{***}	0.1386^{***}	0.1214^{***}	0.2514^{***}
	(0.0076)	(0.0027)	(0.0074)	(0.0042)	(0.0074)	(0.0024)
m	1.3360^{***}	0.3029^{***}	0.9091^{***}	0.1646^{***}	1.0306^{***}	-0.0421^{***}
	(0.0556)	(0.0225)	(0.0678)	(0.0433)	(0.0530)	(0.0204)
LogLik	-1225.92	-2300.58	-1059.49	-1568.19	-1272.27	-2406.4
Observations	1037	1063	1123	1097	1037	1063

Across all measures, the coefficient of A in the data is significantly different from that in *TP* ($p < 0.01$, Welch's t-tests).
* 10%, ** 5%, or *** 1% significance level.

higher m relative to the gradual increases predicted by the *TP*.

Table 4 summarizes the regression results on action-end probability, failure-end probability, and implied threshold to examine the effect of m. The coefficient of m is significant across all measures in the data and much larger than in the *TP*, indicating that m has a strong impact on preventive actions. Hence, Hypothesis 2 is rejected, and the findings are summarized in Result 2.

Result 2. *In the speed-variant treatments, a higher maximum degradation speed leads subjects to take preventive actions at substantially higher failure probabilities.*

This result shows that the change in the maximum degradation speed has a large impact on subjects' actions, which is not predicted by the theory.

5.2 Regression Analysis on Preventive Actions

Next, we perform Probit linear regressions to analyze how subjects make their decisions. The binary variable $X_{s_{i,t}}$ represents the decision at stage $s_{i,t}$ made by participant $i = 1, \ldots, N$, in round $t = 1, \ldots, 20$, with 1 denoting *action* and 0 denoting *wait*. The regression analysis begins with the baseline (BL) model, which includes only a constant term and the failure probability $p_{s_{i,t}}$ at stage $s_{i,t}$. In the learning and stage (LS) model, we introduce two additional explanatory variables: the round t and the stage $s_{i,t}$ for participant i in round t. Table 5 displays the estimation results for both the BL and LS models. Likelihood-ratio tests indicate that the LS model is significantly

Table 5: Linear Probit Model for Preventive Actions with Random Effect on Subjects

Dependent variable: $X_{s_{i,t}}$ *indicates the action taking decision:* $1 =$ *take action and* $0 =$ *wait.*

	F10		F6		F4	
Variable	BL (1)	LS (2)	BL (3)	LS (4)	BL (5)	LS (6)
Constant	-2.9653^{***} (0.1448)	-3.6015^{***} (0.1814)	-3.1499^{***} (0.1581)	-3.7272^{***} (0.1886)	-3.5627^{***} (0.1906)	-3.9725^{***} (0.2182)
$p_{s_{i,t}}$	14.2364^{***} (0.6589)	9.5456^{***} (1.0468)	14.1848^{***} (0.6560)	11.1805^{***} (1.0677)	14.8880^{***} (0.7379)	12.3923^{***} (1.1159)
t		0.0330^{***} (0.0058)		0.0351^{***} (0.0057)		0.0248^{***} (0.0061)
$s_{i,t}$		0.1688^{***} (0.0261)		0.1113^{***} (0.0263)		0.0847^{***} (0.0262)
LogLik	$-1{,}001.19$	-965.19	-994.48	-967.97	-847.04	-833.91
LR test[a]		<0.01		<0.01		<0.01
Observations	3,984	3,984	4,362	4,362	4,484	4,484

	F4-10		F4-15	
Variable	BL (7)	LS (8)	BL (9)	LS (10)
Constant	-3.5919^{***} (0.1835)	-4.0221^{***} (0.2125)	-3.0197^{***} (0.1507)	-3.8442^{***} (0.1985)
$p_{s_{i,t}}$	11.8809^{***} (0.5684)	10.4955^{***} (0.7679)	8.0284^{***} (0.4039)	6.6593^{***} (0.5867)
t		0.0264^{***} (0.0066)		0.0484^{***} (0.0071)
$s_{i,t}$		0.1048^{***} (0.0340)		0.1890^{***} (0.0416)
LogLik	-751.57	-739.46	-717.62	-684.27
LR test[a]		<0.01		<0.01
Observations	3,158	3,158	2,564	2,564

The significant levels are * 10%, ** 5%, and *** 1%.

[a] The p-values of the likelihood-ratio tests (LR tests) for models BL and LS in each treatment.

preferred over the BL model across all treatments (all $p < 0.01$).

The LS model reveals a learning effect across treatments: as subjects complete more rounds, they become increasingly likely to take preventive action. Whether this tendency converges toward or diverges from the theoretical prediction depends on the treatment. Preventive decisions are also strongly shaped by the stage of the process. The positive coefficients of $s_{i,t}$ show that subjects are highly influenced by the stage. In the next section, we examine this *stage effect* in detail.

6 Stage-dependent preventive actions

In this section, we focus on the impact of the stage on preventive action decisions to better understand the behaviors summarized in Results 1 and 2. According to Theorem 1, the optimal rule is to take preventive action once the failure probability exceeds the threshold p^*. The experimental evidence, however, suggests that subjects may not follow this rule. Instead, we allow for the possibility that their preventive actions could be dependent of the stage. We estimate the failure probability that triggers preventive action, denoted by p^{act}, by considering three forms: constant, linear, and quadratic.

The constant form suggests that the failure probability which triggers action p^{act} is independent of the stage, consistent with the optimal threshold described in Theorem 1. The linear form indicates that the failure probability p^{act} increases or decreases linearly with the stage. The quadratic form suggests a convex or concave relationship between the stage and p^{act}. We also tested a higher-degree polynomial relationship, a cubic model, but since the cubic coefficient was not significant in most treatments, it is not included in the main text; the relevant results are available in Online Appendix C. Three models respectively represent the three forms: (1) The *Constant* model, $p^{act} = Constant$, represents $p^{act}_{i,t}$ independent of the stage s; (2) the *Linear* model, $p^{act} = Constant + \gamma_1 s$, represents the linear form; and (3) the *Quadratic* model, $p^{act} = Constant + \gamma_1 s + \gamma_2 s^2$, represents the quadratic form.

In the estimation, we construct $h_i(\theta) = \Phi\left(\frac{p_i - p^{act}_i}{\sigma}\right)$ as the probability that in observation i, subject chooses the preventive action at stage s_i, where $\theta = (Constant, \gamma_1, \gamma_2, \sigma)$ and $\sigma > 0$. The σ represents the standard deviation of estimated errors of which mean is zero. Besides, we incorporate the survival rate to adjust the estimator since the observed actions are conditional on no failure incurring in the previous stages. We employ the full sequential likelihood as follows,

$$L(\theta) = \prod_{i}^{N} [h_i(\theta)]^{y_i^S} \left[\big(1 - h_i(\theta)\big)p_i\right]^{y_i^F} \left[\big(1 - h_i(\theta)\big)(1 - p_i)\right]^{y_i^C},$$

where $y_i^S \in \{0,1\}$, $y_i^F \in \{0,1\}$, and $y_i^C \in \{0,1\}$. In the likelihood function, it shows, conditional on being active at stage s_i, there are three possible outcomes: (1) $y_i^S = 1$ indicating the action taken at stage s_i and the corresponding probability is $h_i(\theta)$; (2) $y_i^F = 1$ indicating no action taken and the failure incurred at stage s_i, where the corresponding probability is $\big(1 - h_i(\theta)\big)p_i$; and (3) $y_i^C = 1$ indicating no action taken nor the failure incurred, where the corresponding probability is $\big(1 - h_i(\theta)\big)(1 - p_i)$.

Table 6 presents the estimates of the three models across the five treatments. Likelihood-ratio tests reveal that the Linear model is not preferred over the Constant model in three treatments (F6, F4 and F4-10). However, the Quadratic model is clearly favored over the Constant model in all treatments (all $p < 0.01$). The significantly positive estimate of γ_2 in the Quadratic model suggests a convex relationship between the stage and the failure probability that triggers action.

Table 6: Estimates of the Probit Model for the Probability Threshold

Dependent variable: $y_i^S = 1$ *indicates action,* $y_i^F = 1$ *indicates wait and failure,* $y_i^C = 1$ *indicates wait and no failure.*

	F10			F6			F4		
Parameter	Constant (1)	Linear (2)	Quadratic (3)	Constant (4)	Linear (5)	Quadratic (6)	Constant (7)	Linear (8)	Quadratic (9)
Constant	0.2476***	0.3864***	0.5872***	0.2710***	0.3109***	0.4864***	0.3075***	0.3239***	0.5556***
	(0.0043)	(0.0084)	(0.0490)	(0.0219)	(0.0184)	(0.0265)	(0.0257)	(0.0137)	(0.0498)
γ_1		-0.0150***	-0.0866***		-0.0039	-0.0618***		-0.0014	-0.0668***
		(0.0003)	(0.0127)		(0.0043)	(0.0069)		(0.0034)	(0.0137)
γ_2			0.0056***			0.0043***			0.0043***
			(0.0008)			(0.0003)			(0.0010)
LogLik	-2024.8	-2016.4	-1975.0	-2187.4	-2186.5	-2145.5	-2179.8	-2179.7	-2128.1
LR test[a]		<0.01	<0.01		0.1815	<0.01		0.6292	<0.01
Observations	3984	3984	3984	4362	4362	4362	4484	4484	4484

	F4-10			F4-15		
Parameter	Constant (10)	Linear (11)	Quadratic (12)	Constant (13)	Linear (14)	Quadratic (15)
Constant	0.3384***	0.3668***	0.5386***	0.4072***	0.4911***	0.8126***
	(0.0064)	(0.0256)	(0.0137)	(0.0085)	(0.0096)	(0.0536)
γ_1		-0.0045	-0.0754***		-0.0164***	-0.1892***
		(0.0053)	(0.0084)		(0.0002)	(0.0251)
γ_2			0.0068***			0.0204***
			(0.0012)			(0.0029)
LogLik	-1835.4	-1834.8	-1812.1	-1698.3	-1695.4	-1655.2
LR test[a]		0.2532	<0.01		0.0159	<0.01
Observations	3158	3158	3158	2564	2564	2564

The significant levels are * 10%, ** 5%, *** 1%.
Standard deviations presented in parenthesis are clustered by sessions.
[a] p-values of the likelihood-ratio tests (LR tests) that compare to the *Constant* model.

To confirm the quadratic relationship, we apply the analysis method from Leif and Uri (2014). We identify a stage such that the failure probability that triggers actions decreases up to that stage, after which it increases: stage 5 in treatments F10, F6, and F4-10, stage 6 in F4, and stage 4 in F4-15. We then fit two linear models: one for the data up to that stage and another for the data from that stage onwards. Table 9 in Online Appendix D gives the estimation results. We find that the fitted slopes in the first linear model are significantly negative for all treatments, while they are positive in the second linear model, significant for all treatments except F10. Recalling that the fitted slope of γ_1 in the linear model of Table 6 is not significant in 4 out of 5 treatments, we see that the negative linear relationship applies only to the early stages, not the entire dataset, further supporting the quadratic relationship.

7 Behavioral Explanations

In this section, we investigate the behavioral explanations for the stage effect identified in Section 6. We examine four factors: (1) risk aversion, (2) loss aversion, (3) probability weighting, and (4) anticipated regret, which are commonly used to explain human decision-making under uncertainty. Since each behavioral model is associated with a specific utility function, we estimate the parameters within these utility functions using the log-likelihood function

$$LogL = \sum_{i=1}^{N} \sum_{t=1}^{20} \sum_{s_{i,j}=1}^{\bar{s}_{i,j}} ln \left[\Phi \left(yy_{s_{i,t}} \frac{AU_{s_{i,t}} - WU_{s_{i,t}}}{\sigma} \right) \right].$$

Here, $AU_{s_{i,t}}$ represents the utility for subject i if they choose to take preventive action in round t at stage $s_{i,t}$. Conversely, if the subject chooses to wait, the utility is denoted as $WU_{s_{i,t}}$, which is an expected value function based on the failure probability $p_{s_{i,t}}$.

(1) Risk Aversion: As subjects face a risk of failure, we consider a risk preference (RISK) model. We assume an exponential utility function to capture risk-averse or risk-seeking behavior, following the form used by Post et al. (2008) and derived from the expo-power family of Saha (1993): $U(x) = (1 - e^{-\alpha x})/\alpha$. The parameter α measures the curvature of $U(x)$: it indicates risk aversion if $\alpha > 0$, risk-seeking behavior if $\alpha < 0$, and risk neutrality if $\alpha \to 0$. In our estimation, we apply

$AU_{s_{i,t}} = U(s_{i,j} - a)$, reflecting that the subject would earn $s_{i,j} - a$ if they choose to take action. The expected utility if the subject chooses to wait is given by $WU_{s_{i,t}} = (1 - p_{s_{i,j}})U(s_{i,j}) + p_{s_{i,j}}U(s_{i,j} - A)$.

(2) Loss Aversion: When a failure occurs, the subject incurs a loss, and the resulting payoff of $\bar{s}_{i,j} - A$ is negative if they have not experienced enough stages to cover the loss. To capture subjects' risk preferences in both gain and loss domains, we consider a loss aversion (LOSS) model. In this model, the parameter α measures the risk attitude in the gain domain, while the parameter β measures it in the loss domain. The utility function is $U(x) = (1 - e^{-\alpha x})/\alpha$ if $x \geq 0$ and $U(x) = \lambda(1 - e^{-\beta x})/\beta$ if $x < 0$, where λ represents the degree of loss aversion. The utilities $AU_{s_{i,t}}$ and $WU_{s_{i,t}}$ are computed analogously to those in the RISK model.

(3) Probability Weighting: Subjects make decisions based on the failure probability at each stage, but they may distort this probability as described by Tversky and Kahneman (1992): people tend to overweight low probabilities and underweight high probabilities. To capture this behavior, the Probability Weighting Function (PWF) model assumes that subjects distort the failure probability through a function $w(p) = \frac{p^\theta}{(p^\theta + (1-p)^\theta)^{1/\theta}}$, where $\theta > 0$, and $w(p) = p$ when $\theta = 1$. For the estimation, we apply $AU_{s_{i,t}} = s_{i,t} - 1$ and $WU_{s_{i,t}} = s_{i,t} - w(p_{s_{i,t}})A$ in the log-likelihood function.

(4) Anticipated Regrets: Humans making decisions under uncertainty may experience regret when realizing that another alternative would have yielded a better outcome (Bell 1982, p.961). To avoid such ex-post regret, they may adjust their decisions ex-ante, a concept known as anticipated regret (AR). Following Filiz-Ozbay and Ozbay (2007), we distinguish two types of regret: winning regret $\delta_w(1 - p_{s_{i,j}})$ and losing regret $\delta_l p_{s_{i,j}}(A - a)$. Winning regret arises when taking action leads to missed opportunities for additional benefits, where $\delta_w \geq 0$ measures the magnitude of the regret, and $1 - p_{s_{i,j}}$ represents the expected benefit from waiting. Losing regret occurs when a failure prompts regret for not acting earlier, where $\delta_l \geq 0$ measures the magnitude of the regret, and $p_{s_{i,j}}(A - a)$ represents the expected payoff that could have been preserved by earlier action. For estimation, we specify $AU_{s_{i,t}} = s_{i,t} - a - \delta_w(1 - p_{s_{i,t}})$ and $WU_{s_{i,t}} = (1 - p_{s_{i,t}})s_{i,t} + p_{s_{i,t}}(s_{i,t} - A) - \delta_l p_{s_{i,t}}(A - a)$ in the log-likelihood function.

Table 7, Panel A, presents the estimation results of the behavioral models based on data from all treatments. Among these models, the AR model achieves the highest log-likelihood value. The positive and significant estimates of δ_w and δ_l indicate that both types of anticipated regret play an important role in explaining preventive decisions. The PWF model yields the second-highest log-likelihood value, suggesting that subjects tend to distort failure probabilities rather than perceive them objectively. The LOSS model fits better than the RISK model, implying that incorporating loss aversion improves explanatory power, while the significant but small α in the RISK model indicates that risk attitude alone cannot sufficiently account for the observed behavior.

Table 7: Estimates of the Profit Model for the Behavioral and Combined Bahavioral Models

Dependent variable: $yy_{s_{i,t}}$ *indicates the action taking decision:* $1 =$ *take action and* $-1 =$ *wait.*

Model	α	β	λ	θ	δ_w	δ_l	LogLik
Panel A: Behavioral Models							
RISK	-0.1082***						-7095.70
	(0.0022)						
LOSS	-0.0259***	-1.4929***	-4.0585***				-5962.57
	(0.0045)	(0.0929)	(0.1760)				
PWF				1.6118***			-5165.30
				(0.0150)			
AR					3.0697***	0.7128***	-4986.04
					(0.1946)	(0.0696)	
Panel B: Combined Behavioral Models							
PWF+AR				1.0625***	6.0330***	2.1515***	-4983.88[a]
				(0.0314)	(0.7025)	(0.3189)	
LOSS+AR	0.1200***	-1.5522***	3.4417***		2.8695***	0.2000***	-4737.35[a]
	(0.0071)	(0.1182)	(0.2567)		(0.1184)	(0.0006)	
PWF+LOSS+AR	0.1064***	-0.4397***	8.7278***	0.7975***	11.6851***	1.1953***	-4683.56[a]
	(0.0078)	(0.1555)	(1.6066)	(0.0556)	(0.5248)	(0.1893)	

All models are estimated with 18,552 observations.
The significant levels are * 10%, ** 5%, *** 1%, respectively;
[a] The pairwise comparisons among the three marked models yield likelihood-ratio test p-values below 0.01.

Given the complexity of the decisions involved, more than one behavioral driver may simultaneously affect the subjects' preventive actions. In the following analysis, we explore a comprehensive explanation by considering combinations of multiple behavioral models. We use the AR model as the primary behavioral model, given its superior performance among the four models. Additionally, we incorporate the PWF and LOSS models as complementary explanations. We do not include the RISK model for two reasons: the LOSS model is more general than the RISK model, and the RISK model shows a poor fit to the data, with an extremely low log-likelihood value compared to the LOSS model. The estimates from the combined models are presented in Table 7, Panel B,

The first combination integrates the PWF and AR models (PWF+AR), showing only a modest improvement in model fit: the log-likelihood increases slightly from –4986.04 in the AR model to –4983.88 in the PWF+AR model (likelihood-ratio test: $p = 0.0376$). The estimated regret parameters, δ_w and δ_l, are larger in the PWF+AR model than in the AR model, indicating that anticipated regret plays a more prominent role when probability distortion is also considered.

The second combination integrates the LOSS and AR models (LOSS+AR). This model yields a substantial improvement in fit, with the log-likelihood rising from –4986.04 in the AR model to –4737.35, suggesting that loss aversion effectively complements anticipated regret in explaining behavior. Notably, the counterintuitive negative estimate of λ in the LOSS model becomes positive when anticipated regret is incorporated, aligning better with behavioral theory. In addition, the estimated curvature parameters are consistent with theoretical expectations: a positive α reflects risk aversion in the gain domain, while a negative β indicates risk seeking in the loss domain.

The final combination model integrates all three components (PWF+LOSS+AR). Likelihood-ratio tests confirm that this model provides the best overall fit among all behavioral and combined alternatives. The convex stage effect can thus be attributed to the joint influence of anticipated regret, loss aversion, and probability weighting. While anticipated regret is the dominant factor, both loss aversion and probability weighting contribute meaningfully to the explanation of preventive actions.

8 Robustness Checks

In our previous analyses, we identified a convex relationship between the stage and the subjective threshold, which can be explained by a combination of anticipated regret, loss aversion, and probability weighting. We now perform robustness checks in three sets of additional experiments. Specifically, we examine: (1) whether the convex relationship and its behavioral explanations persist when the increment of the failure probability is fixed and deterministic; (2) whether the stage itself influences preventive decisions when the failure probability remains constant across stages; and (3) how practitioners make preventive decisions compared to laboratory subjects.

8.1 Deterministic Degradation Process

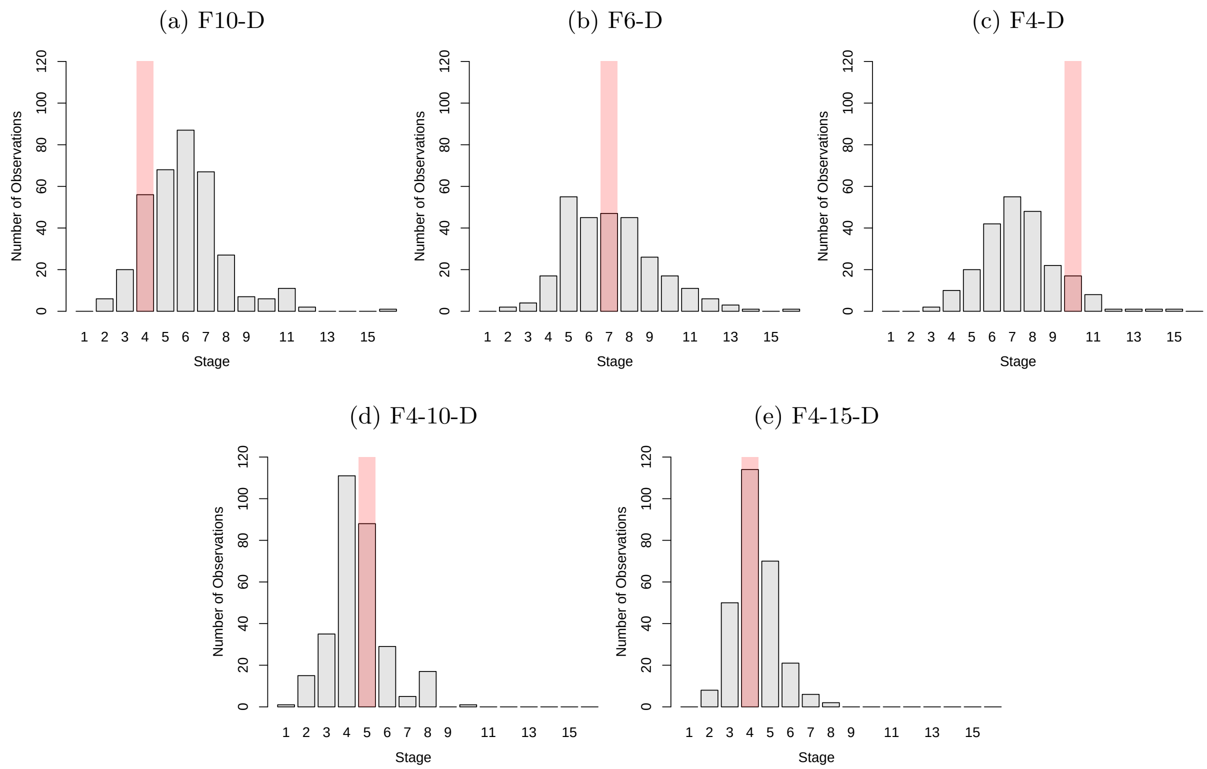
When the failure probability increases stochastically at each stage, subjects face uncertainty about how much it will rise in the next stage. This uncertainty may delay preventive actions if subjects expect only small increases, or may trigger earlier actions if they fear a sharp rise. To remove this effect, the first set of additional experiments replicates the primary design but removes this uncertainty by making the failure probability increase by a fixed increment at each stage. This setting yields five deterministic (D) treatments: F10-D, F6-D, F4-D, F4-10-D, and F4-15-D.

We recruited 30 subjects per treatment, resulting in a total of 150 participants. The experiment was conducted in the same laboratory as the primary study. In the loss-variant treatments, the failure probability was set to 0.025 at stage 1 and increased by 0.025 in each subsequent stage. This increment corresponds to the mean of the uniform distribution $[0, 0.05]$ that we used in the primary experiment. Similarly, in treatment F4-10-D, the failure probability started at 0.05 and increased by 0.05 per stage, and in treatment F4-15-D, it started at 0.075 and increased by 0.075 per stage. Participants were informed of this deterministic process before making their decisions.

We observe behavioral patterns that closely resemble those in the primary experiment. In the loss-variant treatments, the action-end probability gradually increases from 0.1545 to 0.1968 to 0.1930, whereas the theoretical prediction suggests a sharper rise from 0.10 to 0.175 to 0.25. In the speed-variant treatments, the action-end probability increases more steeply from 0.1930 to 0.2454 to 0.3304, while the theory predicts 0.25, 0.25, and 0.30, respectively. The failure-end probabilities confirm these patterns. Overall, these findings lead to the same conclusions as those presented in Result 1 and Result 2. Additional details are provided in Table 10 in Online Appendix F.

Since the optimal action must be taken at a specific stage, Figure 3 compares the observed stages at which subjects acted with the theoretically optimal action stage. In each panel, the red bar indicates the optimal stage, determined by the optimal threshold, while the grey bars represent the observed frequency of action decisions across stages. Note that the total number of action decisions differs across treatments, as there are different failure rates. By examining the distribution of action decisions, the peak of each histogram represents the most frequent stage at which subjects chose to act within a treatment. It is clear that the stage has a huge impact on the action decision. This becomes most clear when looking at the loss-variant treatments in panels (a) to (c): the peak gradually shifts from stage 6 to stage 7, reflecting some influence of A, but the optimal stage shifts from stage 4 to 10.

Figure 3: Action Decisions across Stages in Deterministic Process Treatments



We conduct similar estimations as we did for the original experiment, with the results summarized in Table 11 in Online Appendix F. The convex model continues to outperform both the constant and linear models. Furthermore, we test the robustness of the combined behavioral explanation, with results reported in Table 12 in Online Appendix F; also in this experiment, the combination of probability weighting, loss aversion, and anticipated regret provides the best fit to the data.

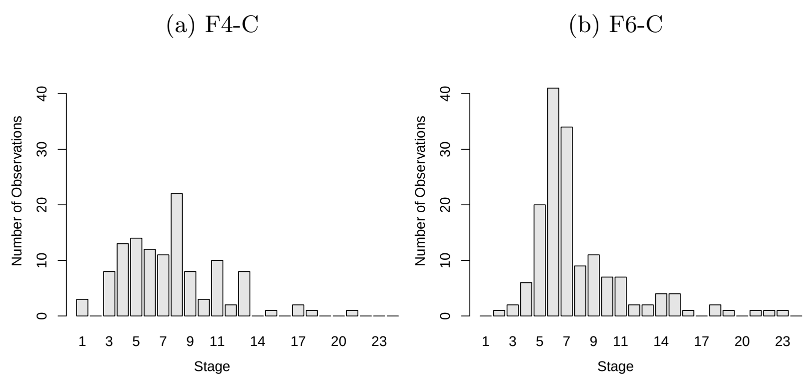
8.2 Constant Failure Probability

In both the stochastic and deterministic degradation processes, the failure probability is inherently correlated with the stage, causing the stage effect to be intertwined with the failure probability.

To disentangle these effects, we conducted a second set of additional experiments in which the failure probability was held constant (C) at 0.1. We consider loss $A \in \{4, 6\}$, resulting in the F4-C and F6-C treatments, respectively. Since the optimal thresholds in both treatments are 0.25 and 0.17, respectively, the optimal decision is to never take preventive action, but to wait for failure. The failure probability is sufficiently low that it typically takes some stages before failure occurs. We recruited 25 subjects for the F4-C treatment and 24 for the F6-C treatment. The maximum end-stage $\bar{s}$ across both treatments was 23.

Figure 4 displays grey bars representing the number of observed preventive actions. In the F4-C

Figure 4: Action Decisions Across Stages in F4-C and F6-C Treatments

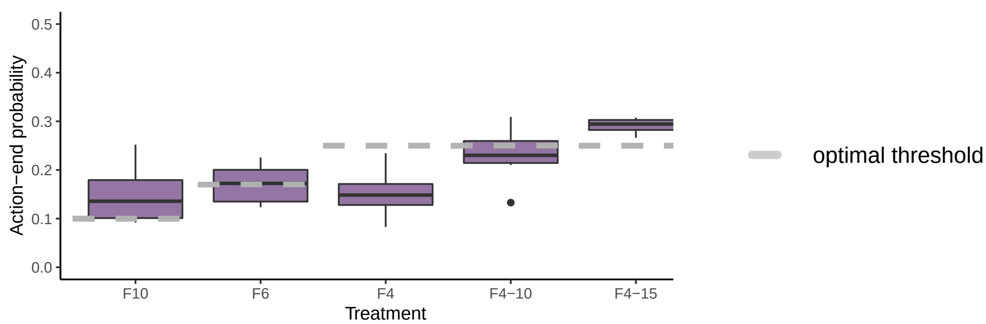


treatment, 119 out of 500 observations were preventive, whereas in the F6-C treatment, 157 out of 480 observations were preventive. The Wilcoxon signed-rank test confirms that the proportions of preventive decisions are significantly different from zero in both treatments ($p < 0.01$). Since a constant threshold would imply either always taking action in the first stage or never taking action at all, the observed preventive actions suggest that subjects' decisions depended on the stage. Furthermore, the figure reveals that preventive actions peak at stage 8 (22 actions) in the F4-C treatment and at stage 6 (41 actions) in the F6-C treatment. The share of preventive actions in F6-C is slightly higher than in F4-C ($p = 0.0696$). Overall, although there is a small difference between F4-C and F6-C, indicating a possible effect of the size of the loss A, the effect is not strong.

8.3 Workshop experiment with practitioners

The third set of additional experiments was conducted on-site during a workshop attended by researchers and practitioners active in CBM. This experiment did not include any monetary incentives. Participants played the game implemented in oTree (Chen et al. 2016) using their mobile phones. The numbers of participants in treatments F10, F6, F4, F4-10, and F4-15 were 8, 8, 7, 8, and 8, respectively. Figure 5 illustrates how the action-end probability varies across treatments. The comparison results are similar to those of the laboratory experiments. The average action-end probabilities do not significantly differ among the loss-variant treatments ($p = 0.494$ for the comparison between F10 and F6, and $p = 0.990$ between F10 and F4). In contrast, there are significant differences among the speed-variant treatments ($p = 0.008$ for F4 vs. F4-10, and $p = 0.017$ for F4-10 vs. F4-15).

Figure 5: Action-end probabilities and the optimal thresholds in the workshop experiment



9 Conclusion

This study investigates preventive actions in a degradation process. We analytically show that the optimal threshold policy increases with the size of the loss but is invariant to the degradation speed. The experimental findings reveal two key behavioral patterns: (1) preventive actions are not sufficiently sensitive to changes in the size of the loss, and (2) a higher maximum degradation speed tends to induce later preventive actions. We next reveal a convex relationship between the subjective threshold and the stage: the threshold decreases in early stages and rises in later stages, which helps explain the observed two behavioral patterns. This convex relationship can be driven by a combination of anticipated regret, loss aversion, and probability weighting. To check the robustness, we conduct three sets of additional experiments and their results confirm our findings.

Our findings have broad applicability in practice. First, our experimental evidence shows that human preventive maintenance decisions deviate from the optimal threshold policy. Technicians in practice may disregard the model-recommended threshold and instead perform maintenance either prematurely or too late, thereby reducing operational efficiency. Second, these deviations are shaped by the structure of the decision process itself, particularly by the frequency of decision opportunities. A high decision frequency can induce premature actions, whereas a low decision frequency may result in delayed interventions. In the context of condition-based maintenance, decision quality may therefore improve if a decision support system is designed to prompt decisions at a moderate frequency—frequent enough to maintain attentiveness, but not so frequent that it encourages unnecessary early actions. Such calibration could help align human preventive behavior more closely with the timing recommended by predictive models.

Our work has thus contributed to the upcoming field of human behavior in sequential decision making, leading to potentially further interesting research, and having a clear relevance for practice. Further research could investigate how the format of information influences decision-making behavior. Such an exploration would complement our analysis with that of Bolton and Katok (2018), who focus on helping individuals make optimal decisions in a cost-loss game. From a practical standpoint, the results of such studies could guide managers on when to present failure probabilities to maintenance planners and in what format.

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Online Appendix

A Proof of Theorem 1

We define the wait function as $w(x, y) = -xA + (1-x)(b+y)$.

Lemma 1. *It holds that $w(x, y)$*

(i) is decreasing in x if $y < A + b$,

(ii) is increasing in y if $x < 1$;

(iii) is smaller than or equal to $-a$ if $y = -a$ and $x \geq \frac{b}{A+b-a}$, and

(iv) it is larger than $-a$ if $y = -a$ and $x < \frac{b}{A+b-a}$.

Proof. We rewrite $w(x, y) = -x(A + b + y) + (b + y)$. If $y < A + b$, we have a positive constant times $-x$ plus a constant, showing that part (i) holds.

We rewrite $w(x, y) = b - x(A + b) + (1 - x)y$. If $x < 1$, we have a constant plus a positive constant times y, showing that part (ii) holds.

If $y = -a$, we have $w(x, y) = -x(A + b - a) + (b - a)$. Then:

$$\begin{aligned} -x(A+b-a) + (b-a) &> -a \\ -x(A+b-a) &> -b \\ -x &> \frac{-b}{A+b-a} \\ x &< \frac{b}{A+b-a}, \end{aligned}$$

showing that parts (iii) and (iv) hold. □

We now define N as the stage at which the failure probability is 1 for the first time that is $p_N = 1$ (and thus $p_s = 1$ for $s > N$). We further define $R(x_s) = \max\{-a, w(x_S, x_{s+1}\}$. We can now write the payoff function at each stage $s > 0$ for a risk-neutral, payoff-maximizing owner as $sb + R(p_s)$.

Because $w(p_N, p_{N+1}) < -a$, $R(p_N) = -a$. Using a recursion starting at N and Lemma 1 (iii), we show that $R(p_s) = -a$ for all $s < N$ with $p_s \geq \frac{b}{A+b-a}$.

We define $\bar{s}$ to be the largest s for which $p_s < \frac{b}{A+b-a}$. Lemma 1 (iv) shows that $w(p_{\bar{s}}, p_{\bar{s}+1}) > -a$ so that $R(p_{\bar{s}}) > -a$.

Because $p_s < p_{s+1}$ for $s \leq \bar{s}$ and $R(p_{\bar{s}}) > R(p_{\bar{s}+1})$, Lemma 1 (i) and (ii) show that $w(p_{\bar{s}-1}, p_{\bar{s}}) > w(p_{\bar{s}}, p_{\bar{s}+1})$, and thus $R(p_{\bar{s}-1}) > R(p_{\bar{s}})$. Recursively, we then show that $R(p_{s-1}) > R(p_s)$ for $1 < s \leq \bar{s}$.

This means that for $1 < s \leq \bar{s}$, waiting is optimal, while for $\bar{s} < s \leq \infty$, taken preventive action is optimal.

B Instruction to F4 treatment

You are participating in an experiment studying how individuals make decisions. Depending on your decisions in the experiment, you can earn money on top of your show-up fee of 10 RMB yuan. Therefore, it is very important to read the instructions carefully. In this experiment, we request you to comply with laboratory rules: switch off your phones and other devices; except for the experimental software application do not open other applications on the desktop computer; and do not talk with the other participants or look at other' computer monitors. If at some point you have a question, please raise your hand and we will address your question as soon as possible.

Today's experiment has 20 rounds. In each round you will earn money which is accumulated to pay you privately in the end. One unit of the experimental currency is equal to one RMB yuan. This experiment is on individual decisions; the outcomes of your decisions will not influence and will not be influenced by other participants.

How are your earnings calculated?

Each round consists of multiple usage stages. At the beginning of each round, in the first stage, you will own a brand-new fictitious machine. Your machine is subject to failure and the probability of failure increases over the stages.

You will earn 1 yuan per stage for the machine usage. In each stage, you will be informed of the probability p of the failure occurring in the current stage. You will decide either "continue" to use or "prevent" failure. If you choose to "prevent" failure, you will pay a preventive cost of 1 yuan to prevent the failure occurrence, and then the current round ends (in other words, no next stage follows anymore). If you choose to "continue", according to the failure probability, there are two possible outcomes: one, if the failure occurs you will pay a loss cost of 4 yuan and the current round ends; two, if no failure occurs you will go on to the next stage.

You can experience stages as many as you can until the failure occurs or you take a preventive action.

When a round ends, your profit will be calculated by the following formula:

(i) if the round ends by your preventive action:

Your cash earning = 1 yuan $\times$ number of usage stages – 1 yuan (preventive cost);

(ii) if the round ends by machine failure:

Your cash earning = 1 yuan × number of usage stages – 4 yuan (loss cost).

How is the failure probability decided?

When you go on to each next stage, the failure probability increases. In the first usage stage, the failure probability p_1 = *random number* which lies in the range of 0 ∼ 5% and every value of random number in this range is equally likely. In the second usage stage, the failure probability increases to $p_2 = p_1 +$ *random number*. This random number is also randomly selected from 0 to 5% where each value has equal likelihood. In general, in stage t, the failure probability becomes $p_t = p_{t-1}+$*random number*, depending on the failure probability in the previous stage plus a random number. Note, each realization of random number is not influenced by any other realizations.

A simple example

Suppose in usage stage 3, the failure probability is 7.56%;

[Situation 1] You choose "prevent" and the round ends. You will earn 2 yuan calculated by 1 × 3 - 1 = 2, according to formula (i);

[Situation 2] You choose "continue" and then failure occurs. This round ends. You will lose 1 yuan calculated by 1 × 3 - 4 = -1 according to formula (ii);

[Situation 3] You choose "continue" and the failure does not occur. Then you enter the usage stage 4 in which the failure probability is 10.78%. You choose "prevent" and the round ends. You will earn 3 yuan calculated by 1 × 4 - 1 = 3, according to formula (i).

How to use the computer program

Figure 6 shows a screenshot of the decision page. On the screen, you can see the current usage stage, current failure probability and previous failure probabilities. By clicking the "continue" button, you find out whether the failure occurs or, if not, you are able to enter the next usage stage; by hitting the "prevent" button, you will pay preventive cost of 1 yuan and the round ends.

There is more information about the occurrence of a failure. After you click the "continue" button, the system will generate a number, the so-called failure index from 0 to 100. If the failure index is larger than the value of the current failure probability, the failure will not occur. For

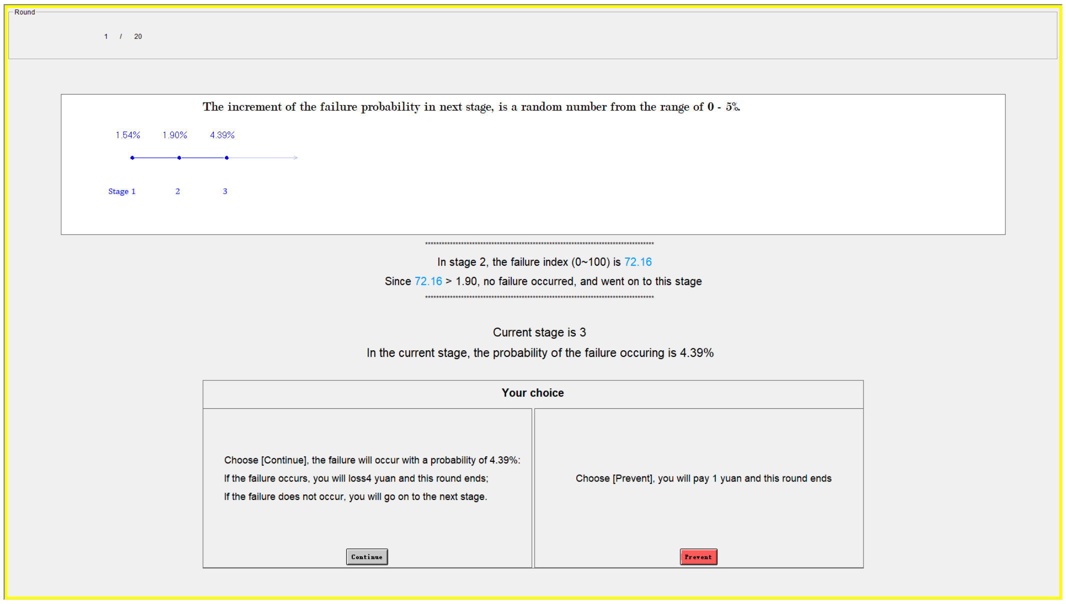


Figure 6: Screenshot (Translated from Chinese)

example, as shown in Figure 1, the failure index in the usage stage 1 is 54.23 which is larger than the value of the failure probability 1.54, and therefore failure does not occur in stage 1. However, if the failure index is less than the value of the failure probability, failure will occur and the round ends.

C Cubic Relationship Test

Table 8: Estimates of the Probit Model for the Probability Threshold - Cubic Relationship[†]

Dependent variable: $yy_{s_{i,t}}$ *indicates the action taking decision:* $1 =$ *take action and* $-1 =$ *wait.*

Parameter	F10	F6	F4	F4-10	F4-15
Constant	0.6422***	0.6347***	0.6303***	0.5598***	0.8238***
	(0.0320)	(0.0505)	(0.1177)	(0.0981)	(0.0369)
γ_1	-0.1154***	-0.1375***	-0.1016**	0.0897	-0.1982***
	(0.0165)	(0.0235)	(0.0422)	(0.0746)	(0.0468)
γ_2	0.0102***	0.0159***	0.0091**	0.0096	0.0226
	(0.0037)	(0.0036)	(0.0045)	(0.0152)	(0.0145)
γ_3	-0.0002	-0.0005***	-0.0002	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0009)	(0.0013)
LogLik	-1974.2	-2138.6	-2126.4	-1812.0	-1655.2
LogLik (from *Quadratic*)	-1975.0	-2145.5	-2128.1	-1812.1	-1655.2
LR test[a]	0.2090	<0.01	0.0650	0.5902	0.8892
Observations	3984	4362	4484	3158	2564

[†] The estimated subjective threshold in this table is $p^{sub} = Constant + \gamma_1 s_{i,t} + \gamma_2 s_{i,t}^2 + \gamma_3 s_{i,t}^3$.
The significant levels are * 10%, ** 5%, *** 1%.
Standard deviations presented in parenthesis are clustered by sessions.
[a] p-values of the likelihood-ratio tests (LR tests) that compare to the *Quadratic* model.

D Quadratic Relationship Test

We employ the analysis of Leif and Uri (2014) to test the quadratic relationship between the subjective threshold and the stage presented in Table 6. Based on the estimates of γ_1 and γ_2, we choose the stage for each treatment: 5 (F10), 5 (F6), 6 (F4), 5 (F4-10), and 4 (F4-15). Next, we fit one linear model up to that stage, and one from that stage onward. Table 9 summarizes the estimated results. Overall, the first part of data where $s_{i,t} \leq M$ shows a negative relationship between the subjective threshold and the stage, and it is significant in all treatments. The second part of the data shows a positive relationship to the rest of the cases, which are significant in most of experiments except for F10 treatment.

Table 9: Linear Probit regressions before and after the pinpointed stage of M

Dependent variable: $yy_{i,t}$ indicates the action taking decision: $1 =$ take action and $-1 =$ wait.

Parameter	F10		F6		F4	
Stage[a]	M =5		M =5		M =6	
	$s_{i,t} \leq M$	$s_{i,t} > M$	$s_{i,t} \leq M$	$s_{i,t} > M$	$s_{i,t} \leq M$	$s_{i,t} > M$
Constant	0.2749***	0.3326**	0.3646***	0.2078***	0.4135***	0.1816***
	(0.0382)	(0.1471)	(0.0607)	(0.0479)	(0.0689)	(0.0529)
$s_{i,t}$	-0.0130**	0.0058	-0.0265***	0.0133***	-0.0250***	0.0197***
	(0.0060)	(0.0113)	(0.0093)	(0.0043)	(0.0089)	(0.0046)
σ	0.0853***	0.3599***	0.1067***	0.1769***	0.1178***	0.1873***
	(0.0117)	(0.1460)	(0.0176)	(0.0349)	(0.0197)	(0.0430)
LogLik	-501.15	-541.61	-494.03	-583.41	-505.11	-428.88
Observations	3072	912	3262	1100	3635	849

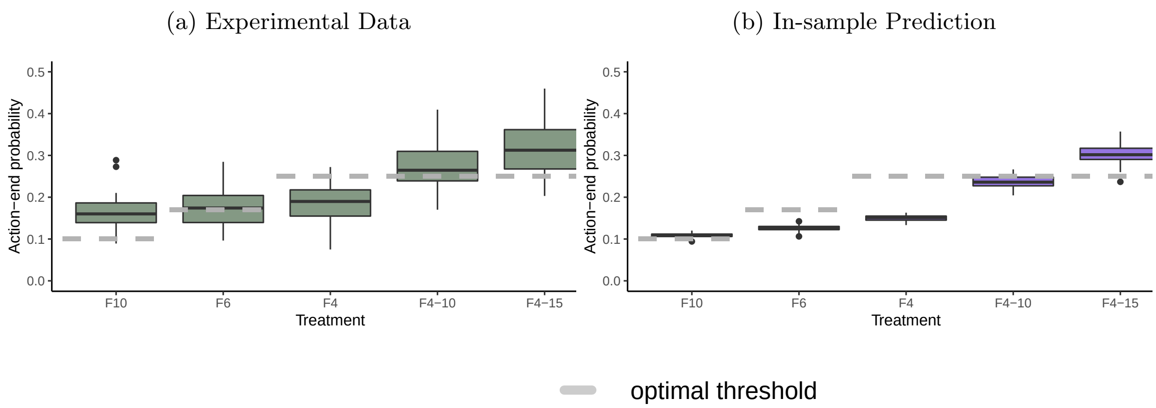
Parameter	F4-10		F4-15	
Stage[a]	M =5		M =4	
	$s_{i,t} \leq M$	$s_{i,t} > M$	$s_{i,t} \leq M$	$s_{i,t} > M$
Constant	0.4203***	0.1421	0.5897***	0.0416
	(0.0407)	(0.0920)	(0.0634)	(0.1532)
$s_{i,t}$	-0.0228***	0.0349***	-0.0598***	0.0754***
	(0.0077)	(0.0132)	(0.0153)	(0.0271)
σ	0.1263***	0.2200***	0.1735***	0.3441***
	(0.0125)	(0.0529)	(0.0189)	(0.1042)
LogLik	-608.28	-211.50	-548.65	-182.59
Observations	2820	338	2278	286

[a] The stage M indicates that stage upto which the threshold decreases.
The significant levels are * 1%, ** 5%, *** 1%, respectively.

E In-sample Prediction

To visualize how the convex threshold predicts the behavior across treatments, we use the estimates from Model (2) in Table **??** to simulate the action-end probabilities for the five treatments. This in-sample approach allows us to assess how the estimates determine the action-end probabilities in the loss-variant treatments and how these probabilities increase as the degradation speed rises. We first calculate the subjective thresholds for each treatment using the estimates, then apply these thresholds to the pre-generated degradation processes used in the lab experiment. Figure 7 depicted the experimental data in (a) and the simulated data in (b).

Figure 7: Action-end Probabilities in Experiment and In-sample Prediction



Each sub-figure indicates the optimal threshold. The simulated average action-end probabilities are 0.1091 (F10), 0.1258 (F6), 0.1501 (F4), 0.2372 (F4-10), and 0.3020 (F4-15). Although there is a significant difference between the experimental data and the simulated results in all treatments (all $p < 0.01$), the model successfully replicates the key findings: (1) the action-end probability does not increase sufficiently as the size of the loss decreases, and (2) the action-end probability sharply increases as the degradation speed rises.

F Results in D treatments

Table 10: Descriptive Statistics for Additional Experiment 1

	F10-D	F6-D	F4-D	F4-10-D	F4-15-D
	Loss-variant treatments				
			Speed-variant treatments		
Payoff	**0.7650*****	**2.7617**	**3.5933**	**1.6567**	**0.9183**
	(1.2302)	(0.9630)	(0.8254)	(0.4883)	(0.4432)
TP	*1.4200*	*2.9750*	*3.8417*	*1.7767*	*1.0983*
	(0.66781)	(0.8287)	(0.7043)	(0.5219)	(0.4733)
End-stage	**5.3950*****	**6.4117****	**6.4533****	**4.1467**	**3.5633*****
	(0.96261)	(1.2538)	(0.9894)	(0.7271)	(0.4844)
TP	*3.7550*	*5.8833*	*6.9567*	*4.0817*	*3.3033*
	(0.1315)	(0.3223)	(0.5385)	(0.2458)	(0.1681)
Failure rate	**0.4033*****	**0.5300*****	**0.6200*****	**0.4967**	**0.5483*****
	(0.15196)	(0.2144)	(0.13170)	(0.1930)	(0.1185)
TP	*0.1483*	*0.3817*	*0.7050*	*0.4350*	*0.4017*
	(0.0609)	(0.1054)	(0.0803)	(0.0993)	(0.1071)
Action-end probability	**0.1545*****	**0.1968****	**0.1930*****	**0.2454**	**0.3304*****
	(0.0366)	(0.0531)	(0.0381)	(0.0632)	(0.0566)
TP[a]	*0.1000*	*0.1750*	*0.2500*	*0.2500*	*0.3000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Failure-end probability	**0.1102*****	**0.1325*****	**0.1441**	**0.1738*****	**0.2187*****
	(0.0223)	(0.0362)	(0.0326)	(0.0443)	(0.0419)
TP	*0.0603*	*0.1012*	*0.1419*	*0.1443*	*0.1673*
	(0.0107)	(0.0100)	(0.0166)	(0.0156)	(0.0215)

Note, standard deviations across participants are in parentheses.
TP denotes the theoretical prediction under risk neutrality.
According to the two-sided t-test, the experimental data are different from the theory benchmark at the * 10%, ** 5%, or *** 1% significance level.
[a] These theory predictions in the deterministic process are constant values.

Table 11: Estimates of the Probit Model for the Probability Threshold - Deterministic Process Treatments

Dependent variable: $yy_{s_{i,t}}$ indicates the action taking decision: $1 =$ take action and $-1 =$ wait.

	F10			F6			F4		
Parameter	Constant (1)	Linear (2)	Quadratic (3)	Constant (4)	Linear (5)	Quadratic (6)	Constant (7)	Linear (8)	Quadratic (9)
Constant	0.2252***	20.6096***	16.1830***	0.3296***	12.5138***	5.5597***	0.3678***	3.5437***	25.0248***
	(0.0170)	(0.596)	(0.7423)	(0.0333)	(0.212)	(0.16328)	(0.0414)	(0.0637)	(7.8273)
γ_1		-2.2632***	-3.3438***		-0.9242***	-0.8588***		-0.2159***	-4.6295***
		(0.236)	(0.2700)		(0.108)	(0.11554)		(0.0308)	(1.2344)
γ_2			0.1855***			0.0421***			0.2501***
			(0.0236)			(0.0090)			(0.0638)
σ	0.0929***	8.4987***	4.4609***	0.1341***	5.0899***	1.5374***	0.1466***	1.4120***	4.9468**
	(0.0111)	(0.380)	(0.2534)	(0.0194)	(0.250)	(0.11357)	(0.0242)	(0.0631)	(2.1792)
LogLik	-921.7969	-921.7969	-878.6338	-859.2690	-859.2690	-820.4236	-743.7936	-743.7936	-660.7439
LR test[a]		0.9989	<0.01		0.9994	<0.01		0.9996	<0.01
Observations	3237	3237	3237	3847	3847	3847	3872	3872	3872

	F4-10			F4-15		
Parameter	Constant (10)	Linear (11)	Quadratic (12)	Constant (13)	Linear (14)	Quadratic (15)
Constant	0.3932***	12.0583***	8.7229***	0.3819***	19.1021***	5.2956***
	(0.0522)	(0.303)	(0.0799)	(0.0218)	(1.808)	(0.1044)
γ_1		-1.4833***	-2.6548***		-3.6767***	-1.7655***
		(0.173)	(0.1706)		(0.546)	(0.1387)
γ_2			0.2248***			0.1560***
			(0.0235)			(0.0202)
σ	0.1853***	5.6848***	2.0956***	0.1244***	6.2220***	0.9988***
	(0.0344)	(0.521)	(0.2968)	(0.0143)	(0.209)	(0.1066)
LogLik	-798.7591	-798.7591	-714.3044	-577.8536	-577.8536	-549.4410
LR test[a]		0.9965	<0.01		1	<0.01
Observations	2488	2488	2488	2138	2138	2138

The significant levels are * 10%, ** 5%, *** 1%.
Standard deviations presented in parenthesis are clustered by subjects.
[a] p-values of the likelihood-ratio tests (LR tests) that compare to the *Constant* model.

Table 12: Estimates of the Probit Model for Combined Behavioral Models (Pooled Data) - Deterministic Process Treatments

Dependent variable: $yy_{s_{i,t}}$ indicates the action taking decision: $1 =$ take action and $-1 =$ wait.

Parameter	Quadratic Model	PWF+AR	LOSS+AR	PWF+LOSS+AR
Constant	0.7447			
	(0.0350)			
γ_1	-0.1086			
	(0.0081)			
γ_2	0.0074			
	(0.0005)			
α			0.0959	0.1199
			(0.0099)	(0.0097)
β			-0.1171	-0.1429
			(0.0361)	(0.0531)
λ			3.2253	6.3863
			(0.4306)	(0.9099)
θ		0.9748		1.4318
		(0.0299)		(0.1740)
δ_w		3.2977	8.4115	7.6659
		(1.0173)	(0.8606)	(1.0885)
δ_l		0.7681	1.0211	0.8020
		(0.4313)	(0.1630)	(0.0892)
σ	0.2148	1.8058	4.5321	4.4069
	(0.0100)	(0.4304)	(0.5721)	(0.7747)
Log-Likelihood	-3808.72	-3966.88	-3813.70	-3800.93
Observations	15582	15582	15582	15582

The significant levels are * 1%, ** 5%, *** 1%, respectively;
LR tests suggest the order of preferred models as follow: Model (10) $\succ$ Model (7) $\succ$ Model (9) $\succ$ Model (8).
All p-values are <0.01.