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The joint effect of feedback order and reward schemes on prevalence-induced perceptual decisions

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Both target prevalence and associated rewards can bias perceptual decisions. Prior studies have shown that shifts in target prevalence can alter decision criteria, and that feedback can further modulate these effects. The present study aims to investigate whether reward schemes similarly interact with feedback to shape perceptual decision biases. In Experiment 1, participants were assigned a categorization task with or without trial-by-trial feedback, and targets in low- and regular-prevalence conditions yielded the same expected value. The impact of the reward scheme was further investigated in Experiment 2 by introducing severe penalties for misses. Contrary to our expectations, the results suggested that reward schemes had minimal effects in both experiments. Importantly, the sequence in which feedback was given proved crucial. The participants who initially did not receive feedback made more liberal decisions than did those who first received feedback but later had it removed. These findings offer valuable insights for optimizing performance across varying target prevalence scenarios in future research.

Keywords Prevalence effect, Criterion shift, Perceptual decision-making

Visual search in real-world scenarios often involves low-prevalence targets, which are associated with an increased likelihood of missed detection[1,2]. This prevalence effect is particularly challenging to mitigate[3]. Decision-makers may fail to detect low-prevalence targets regardless of their level of experience[4] or the format of the stimuli[5–8], and such errors can occur in both real-life situations and controlled laboratory settings[9]. Signal detection theory (SDT)[10], which provides a framework for understanding decision-making accuracy, explains that misses occur when the response to a target-present (signal) distribution falls below the decision criterion *c*. This means that the low-prevalence effect (LPE) can be attributed to a lower quitting threshold, which leads to faster "target-absent" responses and the use of conservative criteria when identifying the target[11].

A recent study by Levari et al., on the other hand, showed that participants may employ liberal criteria involving low-prevalence targets rather than conservative ones. In a blue-purple color categorization task, Levari et al. reported that participants were more inclined to label ambiguous stimuli as blue when the probability of seeing a blue stimulus decreased from 50 to 6%[12]. This "prevalence-induced concept change" (PICC) effect provides evidence that challenges the conventional interpretation of criterion shifts in the LPE[7,8], which leads to the hypothesis that ambiguous stimuli will be identified less frequently as "blue" when participants encounter the "blue" stimulus significantly fewer times.

To resolve the observed conflict in criterion shifts, Lyu et al. proposed that feedback might have an important effect on decision-making processes under low-prevalence conditions[13]. They found that when participants received feedback on their performance during the blue–purple categorization task, they were more cautious in identifying targets, resulting in a higher incidence of misses, as shown in the LPE. Conversely, in the absence of feedback, participants demonstrated a greater number of responses confirming the existence of targets, as shown in PICC.

While feedback has been proposed as an effective method for mitigating the prevalence effect in previous research[3], observers in real-world settings, such as medical image diagnosis and security screening, typically do not receive explicit feedback. More importantly, implicit evaluation—such as rare events (e.g., tumors and explosives), which are typically harder to detect and carry more severe consequences—can also prompt decision-

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makers to adopt a more cautious approach when rejecting non-targets. A target's perceived importance may also alter the decision based on the observer's level of expertise. For example, expert radiologists are more likely to overlook prominent but less critical lesions (e.g., bulla) than to overlook rarer yet more serious conditions (e.g., cancer or ground-glass nodules)[14], indicating a unique ability to detect these conditions. A criterion shift similar to that of PICC in the assessment of hip fractures—characterized by a more liberal response criterion in low-prevalence conditions—was also evident in our previous research, with nonexperts rarely encountering hip fracture patients[15]. We hypothesized that nonexperts may disproportionately emphasize the consequences of missed errors. Furthermore, Zhang and Houpt[8] provided direct evidence that penalizing misses led to an increase in "target-present" responses, ultimately resulting in a significantly more liberal criterion. Overall, both the likelihood of encountering a target (i.e., base rate) and the outcomes associated with a decision (i.e., payout)[16] suggest that individuals may prioritize maximizing the expected value over accuracy, leading to criterion shifts that can diverge from the LPE.

Overview of the present study
Previous research has suggested that a shift to low target prevalence can lead to either a conservative criterion (i.e., LPE) or a liberal criterion (i.e., PICC), depending on whether feedback was presented. Building on this, our current research aimed to explore the combined effects of rewards associated with decisions and feedback presentation on amplifying or mitigating PICC or the LPE. In Experiment 1, people were asked to perform a color categorization task[13] in which the goal of maximizing expected values would lead to the same (optimal) criteria for both low- and regular-prevalence conditions. We hypothesized that, in addition to the observed LPE or PICC induced by the presence of feedback, the goal of receiving more payoffs would mitigate the influence of feedback. Therefore, the shifts would be less significant compared to previous research where rewards were not introduced[12,13]. To further explore the extent to which criterion shift can be influenced by rewards, Experiment 2 introduced substantial penalties for missed targets, simulating the critical consequences often encountered in real-world low-prevalence search tasks[5,9]. Consequently, when participants were expected to exhibit the LPE upon receiving feedback, we hypothesized that a focus on minimizing misses would prompt them to adopt more liberal criteria in low-prevalence conditions, thereby reducing or potentially reversing the LPE, leading to an observation similar to that with PICC.

Experiment 1
Methods
Participants
Following Lyu et al.[13], we targeted a minimum of 30 participants for each condition in our designed experiments. In total, 86 university students (75 females and 11 males, aged 20.49 ± 1.55 years) at Central China Normal University were recruited for Experiment 1. All the participants reported normal or corrected-to-normal vision. The participants received RMB 35 (approximately $5) as a monetary reward for their participation. In the designated reward conditions (described below), the participants received points based on their responses and were further incentivized with an additional RMB 35 if they ranked within the top 15% based on their earned cumulative points. All the participants were given a written informed consent form approved by the Human Research Ethics Committee of Central China Normal University (Protocol code: CCNU-IRB-20240325A). All the procedures performed in the studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Experimental design
Our experiment included the target prevalence (regular prevalence: 50%; low prevalence: 10%) and feedback presence (feedback present, feedback absent) as the within-subject design. Furthermore, we contrasted the equal-value-reward condition with the no-reward condition as the between-subject factor, with participants in the no-reward condition not incentivized as in Lyu et al.[13].

To equalize the expected value across the two prevalence conditions, in scenarios where the participants earned cumulative points based on their performance, we applied a normative model of decision-making[17]. In this model, the proportion of choosing option A is determined by the x_i values of the possible payoffs, as well as the association probability p_i.

$$\Pr\{\text{Choose A}\} \propto \sum{}_{\mathrm{i}}\mathrm{x_i p_i} \tag{1}$$

If a target is correctly detected (i.e., hit in signal detection theory) with an assigned value of 1 point when the target prevalence is 0.5, the target should be assigned a value of 5 points when the target prevalence is 0.1 to maintain the same expected value in both prevalence conditions ($1 \times 0.5 = 5 \times 0.1$). Similarly, correctly rejecting a foil (i.e., correct rejection) that is 1 point with a target prevalence of 0.5 corresponds to 5/9 points given more expected rejections in 0.1 target prevalence conditions ($1 \times (1\text{-}0.5) = (1-0.1) \times \frac{5}{9}$). Given the optimal criterion, *C* is given by

$$c_{optimal} = \frac{1}{d'}[\log(\frac{x_{CR} - x_{FA}}{x_H - x_M}) - logit(p)] \tag{2}$$

where p, x_{CR}, x_{FA}, x_H, and x_H represent the outcome probability and expected values of correct rejections, false alarms, hits, and misses, respectively. As a result, our designed payoff matrix in the equal value condition

	Hits	False alarms	Misses	Correct rejections
Regular prevalence (50%)	+ 1	0	0	+ 1
Low prevalence (10%)	+ 5	0	0	+ 0.56(~ 5/9)

Table 1. Payoff matrix for reward schemes in experiment 1 for the *equal-value* condition.

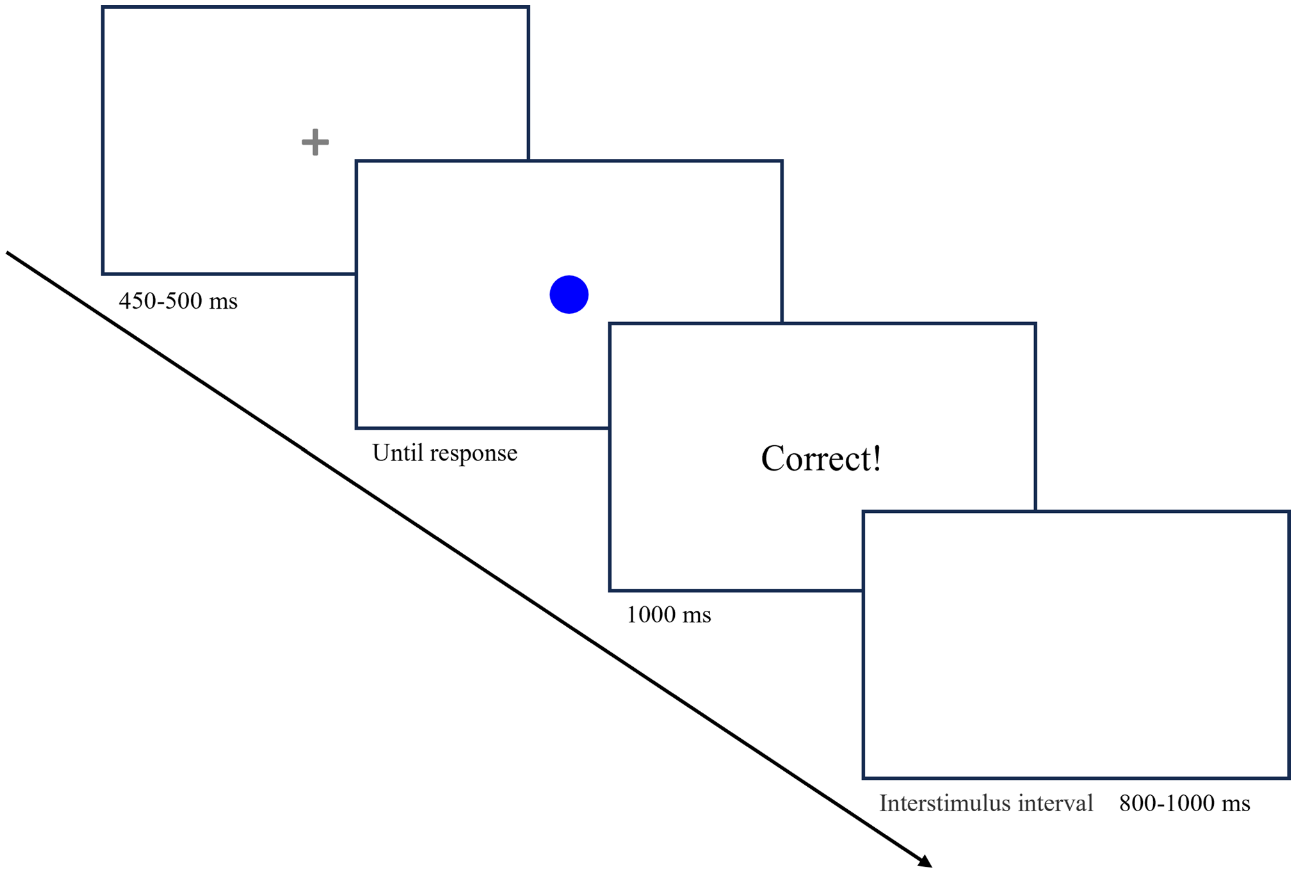

Fig. 1. Procedure of a trial in Experiment 1 in the no-reward condition, in which the participants received feedback on their performance but had no associated payoffs.

(Table 1) leads to the same placed optimal criteria (*c*) on the basis of the change in prevalence between the regular- and low-prevalence conditions, assuming that the overall target discriminability (*d'*) remains constant.

To summarize, our current design included three manipulations aimed at influencing decisions: reward schemes (no reward/equal value reward), prevalence (regular/low), and feedback display (present/absent). In addition, the within-subject factor—the sequence of feedback display—was counterbalanced across subjects. Figure 1 depicts an example trial. Each trial began with a fixation cross displayed at the center of the screen, varying from 450 to 500 ms. Then, the test stimulus was presented to the participants to make a judgment until they responded. The participants were instructed to press "J" if the stimulus was blue and "F" if the stimulus was "not blue" using the keyboard. During the feedback session, the participants also received feedback for 1000 ms along with their points if they were in the equal-value condition, followed by a blank interstimulus presentation for 800 ms to 1000 ms.

Materials

The experiment was programmed using PsychoPy[18]. The stimuli were based on Lyu et al.[13] with a subtended visual angle of 4.8° × 4.8°. In each trial, the color of the stimuli was chosen randomly from a continuous blue-purple spectrum with 100 discrete RGB values (most purple: RGB 100-0-155; most blue: RGB 1-0-254) and was divided into two categories: "blue" (RGB 50-0-205 through 1-0-254) and "nonblue" (RGB 100-155 through 51-0-204). The stimuli were presented on a 24" VIEWPixx/EEG display with a screen resolution of 1920 × 1080 pixels and a refresh rate of 120 Hz. The participants performed the task with a viewing distance of approximately 60 cm.

Procedure
To minimize the potential influence of carryover effects of the payoffs and experience exposure to the design of prevalence conditions, the participants were randomly assigned to either the equal-value or the no-reward condition as a between-subjects design. The study consisted of 12 blocks, separated into 6 blocks for feedback-present trials and 6 blocks for feedback-absent trials, with each block consisting of 100 trials. Following the approach used by Lyu et al.[13], the participants completed two blocks for the regular-prevalence condition (50%) and four blocks for the low-prevalence condition (10%) in a fixed sequence for each feedback display condition. The design of the unbalanced number of blocks resulted in more observations of targets for the low-prevalence condition.

The participants practiced 10 trials before the formal start of the experiments. Whether the participants started with the feedback display was counterbalanced across the participants. The equal-value-reward condition did not inform participants of the payoffs ahead. They received payoffs associated with their responses on each trial (when in the feedback-present blocks) as well as the accumulated payoffs during the block interval to help them track their cumulative earned points. The entire experiment lasted for approximately 1 h. To ensure that the participants actively participated in the study, we considered responses that were faster than 200 ms or slower than 3000 ms as invalid responses. Two participants who had more than 10% careless trials (i.e., 120 trials) were excluded from further analysis. This led to 43 participants in the no-reward condition and 41 participants in the equal-value-reward condition.

Results
We collected the participants' responses and response times (RTs) for each trial. We used the bhsdtr2 package in R for hierarchical Bayesian signal detection analysis to compute criteria (*c*) and discriminability (*d'*).

Following Lyu et al.[13], the order of the presentation of feedback was also included in our data analysis. Figure 2 illustrates the relationship between the percentage of blue responses and the binned stimulus color in both the 10% and 50% target prevalence blocks, separated into 2 reward schemes (no-reward/equal-value-reward) × 2 received feedback order (feedback-first/feedback-second), equal to 4 different panels. Figure 2 suggests that our data replicated the previous finding that feedback influenced the shift in the direction of the criteria, as the feedback-absent condition (depicted by the dotted line) resulted in PICC, and the feedback-present condition (depicted by the solid line) resulted in the classic LPE.

To further analyze the participants' criteria and discriminability in SDT, we fitted the participants' responses in a Bayesian hierarchical SDT analysis model in R following Paulewicz and Blaut[19]. For the SDT analysis, "blue" responses to binned stimulus color categories 1–5 were defined as false alarms, and categories 6–10 were defined as hits (true positive responses). The model was estimated using a Markov chain Monte Carlo (MCMC) sampler with 15 chains of 5000 iterations and a warm-up of 2000. This ensured that we obtained a minimum of 10,000 for the effective sample size (ESS) for the parameter distribution assumption[20] for the reliability assessment. In addition, the R-hat values for the sampled estimated parameters were assessed to ensure that they were below 1.01, indicating good convergence.

The Bayesian methodology obtains an estimation of the parameters of the posterior distribution by including both observed data and prior beliefs. Our current research adopted the prior assumption outlined in Meredith and Kruschke[21], which encompassed a wide range of hypothesized observed responses. Owing to the computational ability to compare the appropriate model in our current Bayesian SDT analysis implementation, the results of our interpretation of the manipulative effects included four main factors and their interactions.

We reported the posterior distribution of each parameter of interest by presenting its model value (median) along with the 95% highest density interval (HDI[21]). The posterior value, which includes the highest probability density, represents the most credible estimates. The 95% HDI, therefore, suggests that there is a 95% chance that the true parameter value falls within this range. In this methodology, we assert that a difference exists between the two posterior distributions if their highest density intervals (HDIs) do not intersect.

Figure 3 reveals the median and HDIs of the posterior distribution from the full model, which includes all the factors and interactions for the criteria. Consistent with previous research by Lyu et al.[13], the feedback display had a significant effect. As the target prevalence decreased from 50% to 10%, there was a noticeable pattern of the criteria becoming more liberal without any feedback (as seen by a decrease in the score, regular prevalence 95% HDI [-0.54, 0.98]; low prevalence 95% HDI [-0.85, 0.63]; Fig. 3, red line), as predicted by PICC. Conversely, the presence of feedback led to more conservative criteria (indicated by a higher score: regular prevalence 95% HDI [-0.26, -0.08]; low prevalence 95% HDI [0.26, 0.44]; Fig. 3, green line), which was consistent with the LPE.

Furthermore, the sequence of the feedback display had a substantial impact and interacted with whether the feedback was present. The trend in the criteria was the same for both conditions when feedback was present, regardless of whether it was equal-value or no-reward, in both the feedback-first (Fig. 3, green line, left panel; regular prevalence 95% HDI [− 0.27, − 0.09], low prevalence 95% HDI [0.26, 0.43]) and feedback-second (Fig. 3, green line, right panel; regular prevalence 95% HDI [− 0.24, − 0.07], low prevalence 95% HDI [0.27, 0.45]) conditions. However, in the absence of feedback, participants who received feedback initially exhibited more conservative criteria (Fig. 4, red line, left panel; regular prevalence 95% HDI [0.81, 1.00], low prevalence 95% HDI [0.47, 0.64]) than those who received feedback thereafter (Fig. 4, red line, right panel; regular prevalence 95% HDI [− 0.55, − 0.37], low prevalence 95% HDI [− 0.87, − 0.67]).

In contrast to our initial hypothesis, we were unable to find evidence to substantiate the notion that the participants' criteria would shift less when they were trying to gain more payoffs in the equal-value-reward condition. As revealed in Table 2, the range of criterion shifts in the equal-value-reward condition was approximately equivalent to the shifts in the no-reward condition. This was true for both the feedback-present and feedback-absent conditions, regardless of the sequence of the feedback presence.

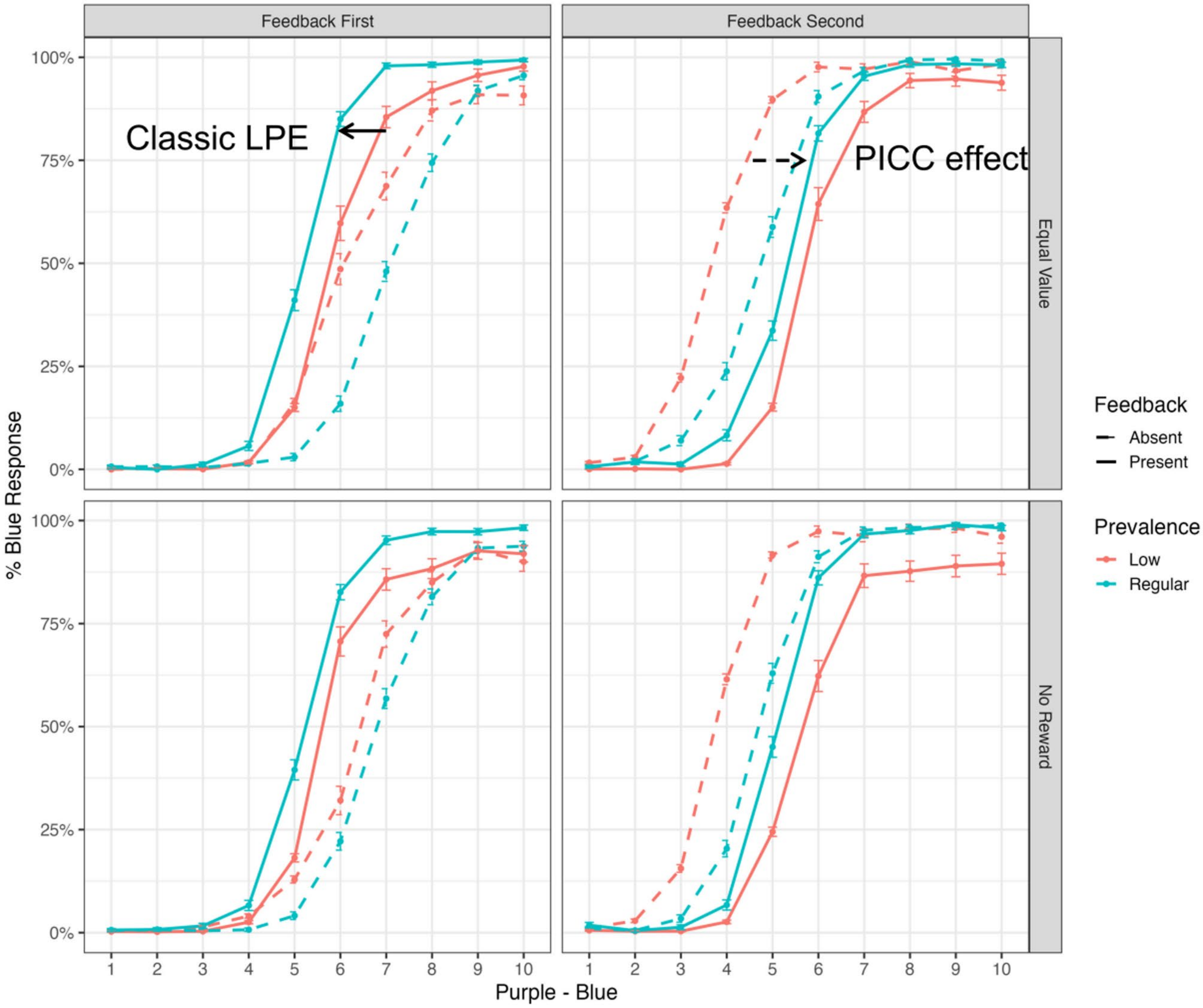

Fig. 2. The percentage of blue responses in Experiment 1 as a function of the binned category (explained in the text), target prevalence, and feedback display (absent: dotted line, present: solid line) for the feedback-first and feedback-second groups varied by the two different reward schemes (no-reward and equal-value-reward payoffs).

Figure 4 presents the median and HDIs of the posterior distribution from the full model for discriminability. The results indicated that there was no noticeable distinction between the regular-prevalence and low-prevalence conditions, except in the equal-value-reward condition when feedback was absent (Fig. 4; red line, right top panel). In this case, participants who received feedback second in the regular-prevalence condition (95% HDI [2.78, 3.07]; Fig. 4, red line, right top panel, right column) demonstrated superior discriminability compared with that in the low-prevalence condition (95% HDI [2.27, 2.59]; Fig. 4, red line, right top panel, left column). Furthermore, in the equal-value-reward condition, when the target prevalence was low, participants performed better when feedback was not provided than when it was not provided, regardless of whether the feedback was provided first (feedback present: 95% HDI [2.83, 3.12]; feedback absent: 95% HDI [2.49, 2.75]; Fig. 4, left top panel, left column) or second (feedback present: 95% HDI [2.70, 2.99]; feedback absent: 95% HDI [2.26, 2.59]; Fig. 4, right top panel, left column).

Discussion

Our Experiment 1 was built on the research of Lyu et al.[13] by adding a change in rewards to the value that the participants expected from the same low- and regular-prevalence conditions. Like Lyu et al.[13], our findings suggested that feedback influenced participants' perceptual decisions: as the prevalence changed from regular to low, the participants shifted their criteria significantly, and whether feedback was given affected the direction of this shift in line with findings of LPE and PICC. Additionally, the order in which feedback was given substantially affected the feedback-absent criteria. The participants assigned to the feedback-second condition had more liberal criteria when the feedback was absent than did those assigned to the feedback-first condition.

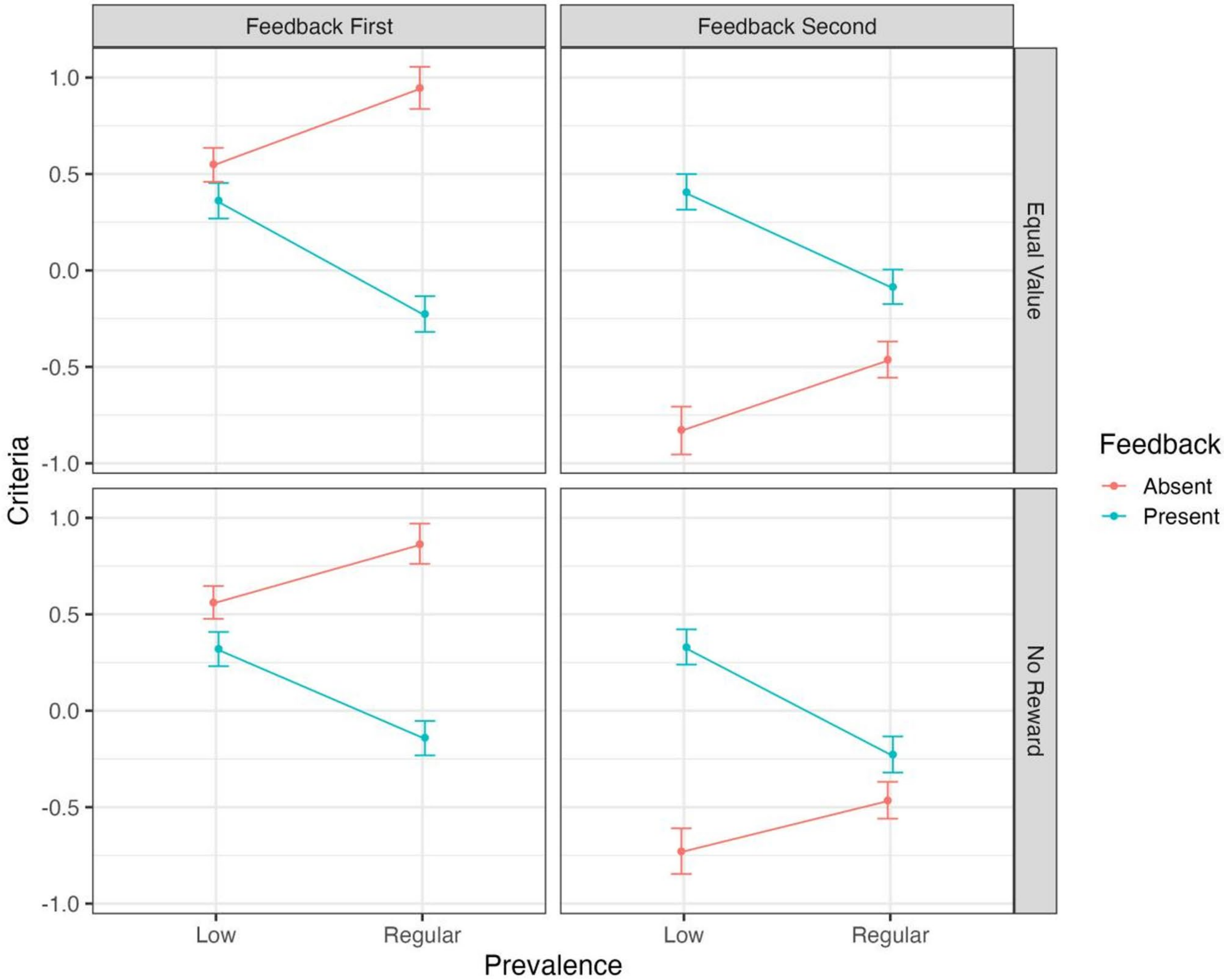

Fig. 3. The 95% HDI of the posterior distribution (median in dots) of the group-level criteria in Experiment 1.

The results suggested that participants who did not receive feedback initially were more likely to give "target-present" answers, whereas participants who had feedback first might still experience a carryover effect when the feedback was removed.

Contrary to our expectation, we found no evidence suggesting that the equal-value design restricted the criterion shift induced by the prevalence change. However, there was an evident trend in which the trial-by-trial feedback led to better discriminability (Fig. 4) when the prevalence was low, irrespective of the order in which the feedback was given; this difference was not evident in the no-reward condition. While this difference between the no-reward and equal-value conditions could have resulted from the competitive rewarded scenario, it is also possible that the participants' payoff points provided redundant feedback information[22]. Together, we find that equalizing the expected value of SDT outcomes in the low- and regular-prevalence conditions had only minor effects on performance without reward considerations. Given that the nonlinear utility function may have led participants to evaluate the reward outcomes differently from the objective reward value[16], Experiment 2 further investigated the influence of the reward schemes by imposing penalties for erroneous responses, as an emphasis on misses closely resembled real-life search tasks that are linked with low prevalence.

Experiment 2

Methods

Participants

Ninety-three participants (44 males and 49 females, aged 21.46 ± 2.59 years) at National Cheng Kung University volunteered to participate in Experiment 2. All the participants reported normal or corrected-to-normal visual acuity. They received NTD 200 (approximately $6.17) for their participation and were motivated by receiving an extra NTD 200 for being in the top 15% on the basis of the points they collected within their assigned payoff condition (explained below, Table 3). All the participants were given a written informed consent form approved by the Human Research Ethics Committee of Taipei Medical University (protocol code: TMU-IRB-N202202034). All the procedures performed in the studies involving human participants were in accordance with the ethical

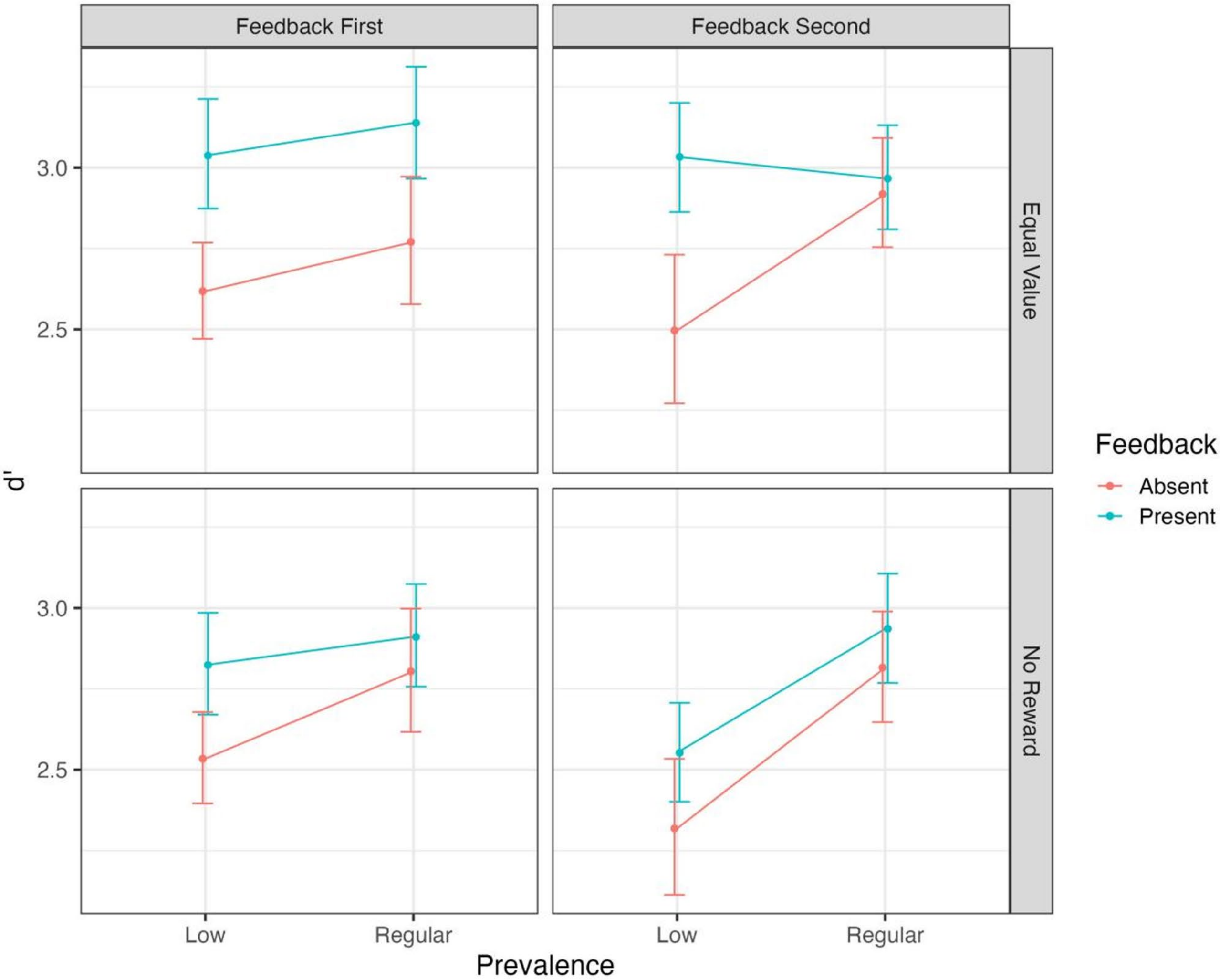

Fig. 4. The 95% HDI of the posterior distribution (median in dots) of the group level d' in Experiment 1.

Feedback	Feedback first		Feedback second	
	Present	Absent	Present	Absent
Reward				
Equal-value	[− 0.64, − 0.40]	[0.23, 0.47]	[−0.63, − 0.40]	[0.17, 0.43]
No-reward	[− 0.64, −0.41]	[0.23, 0.47]	[−0.63, − 0.40]	[0.18, 0.44]

Table 2. Criterion shift (credible mean differences) as a function of different conditions in experiment 1. To calculate the criterion shift, we randomly selected 10% of data points from the posterior distribution and determined the differences. This process allowed us to measure the shift between the two sampled prevalence conditions. The iteration was then repeated 1000 times to obtain the 95% HDI, representing the potential range of the shift between the two conditions.

	Hits	False alarms	Misses	Correct rejections
Neutral	+ 1	− 50	− 50	+ 1
Penalty	+ 100	− 50	− 900	+ 1

Table 3. Payoff matrix of reward schemes in experiment 2.

standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Experimental design, stimuli, and procedure
The stimuli and general procedure were the same as those in Experiment 1 except for the payoff matrix in reward schemes design. Experiment 2 designed two payoff matrices following the previous study for the regular- and low-prevalence conditions[8,16]: In the *neutral* condition, [V(CR) - V(FA)]/[V(H) - V(M)] = 1; therefore, the participants were expected to shift their criteria based on their experience of prevalence conditions rather than the payoffs (Eq. 2). In the *penalty* condition, [V(CR) - V(FA)]/[V(H) - V(M)] = 0.051; in this way, the "optimal criteria" were determined by the payoffs rather than the target prevalence. The goal of Experiment 2 was to test the extent to which the criterion shift could be influenced by the payoff matrices and whether severely penalized miss errors could ameliorate (or even reverse) the prevalence-induced perceptual changes. In summary, the design included three factors: reward schemes (neutral/penalty), prevalence (regular/low), and feedback display (present/absent). The within-subject factor (i.e., the sequence of feedback display) was counterbalanced among the subjects.

The participants were randomly assigned to the penalty and neutral conditions, starting with either the feedback-present or feedback-absent condition (i.e., feedback first or feedback second). The experiment was run on a 24-inch liquid crystal display (LCD) with a screen resolution of 1920 × 1080 pixels and a refresh rate of 60 Hz. The participants performed the task at a viewing distance of approximately 60 cm with the task stimuli extended to a visual angle of 2.86° × 2.86°. Two participants were excluded from the data analysis based on the same exclusion criteria as in Experiment 1. In total, 49 participants were included in the neutral condition, whereas 42 participants participated in the penalty condition.

Results
The same analysis was performed as in Experiment 1. A similar hierarchical Bayesian signal detection analysis was performed for the collected participants' responses.

Figure 5 illustrates the proportion of "blue" responses based on different colors of the stimuli for low- and regular-target-prevalence blocks, considering the feedback display, order of feedback presentation, and reward schemes. As in Experiment 1, the likelihood of participants giving "target-present" answers was determined by the target prevalence as well as the presence or absence of feedback. As the prevalence shifted from regular to low, the participants exhibited an increased tendency to provide target-present responses in the absence of feedback presentation while demonstrating a decreased likelihood of such responses when feedback was available.

To validate the observations in Fig. 5, we employed our hierarchical SDT model as in Experiment 1. The model incorporates all the main factors and their potential interactions when fitting participants' responses. The results showed that the criteria (*c*) mostly matched the patterns observed in PICC and the LPE (Fig. 6), except for participants who received feedback later and were in the neutral condition. In this situation, there was only a small change in the criteria (regular prevalence: 95% HDI [– 0.75, – 0.48]; low prevalence: 95% HDI [– 0.99, – 0.69]; Fig. 6, top right panel, red line).

Like in Experiment 1, the feedback order was essential in determining the responses when feedback was absent. In the neutral condition, participants who received feedback second had more liberal criteria (low prevalence: 95% HDI [– 0.99, – 0.69], regular prevalence: 95% HDI [– 0.75, – 0.48]; Fig. 6, top right panel, red line) than did participants who received feedback information at the beginning of the task (low prevalence: 95% HDI [0.48, 0.77], regular prevalence: 95% HDI [1.03, 1.34]; Fig. 6, top left panel, red line). A similar trend was noted among participants assigned to the penalty condition when the feedback was given second (low prevalence, 95% HDI [– 1.26, – 0.85]; regular prevalence: 95% HDI [– 0.65, – 0.34]; Fig. 6, bottom right panel, red line) as opposed to when it was given first (low prevalence: 95% HDI [– 0.09, 0.20]; regular prevalence: 95% HDI [0.65, 0.96]; Fig. 6, bottom left panel, red line).

We hypothesized that penalizing misses would result in more liberal criteria, causing participants to reply "target-present" more frequently. The sampled posterior distribution suggested that this was the case for participants in the feedback-first condition when feedback was absent (the red line in the left panel, Fig. 6; neutral: low prevalence 95% HDI [0.48, 0.77], regular prevalence 95% HDI [1.03, 1.35]; penalty: low prevalence 95% HDI [– 0.09, 0.20]; regular prevalence 95% HDI [0.65, 0.95]). However, the impact of the reward schemes was not apparent to participants who received the feedback information second, nor did the reward scheme influence the criteria when feedback was present. Table 4 provides additional information on whether the penalty helped ameliorate the induced criterion shift. When feedback was absent, the criterion shift was less pronounced in the neutral condition than in the penalty condition.

Figure 7 shows the 95% HDI of the sampled posterior distribution for discriminability (*d'*). As indicated, the discriminability showed minimal variation in response to the prevalence change. The performance of the participants assigned to the feedback-first condition for the penalty reward was substantially lower in the low-prevalence condition (95% HDI [2.26, 2.58]) than in the regular-prevalence condition (95% HDI [2.85, 3.28]) when feedback was not provided (Fig. 7, left bottom panel, red line). Furthermore, the participants exhibited greater discriminability when feedback was present. This comparative difference was observed when the target prevalence was low for participants in the feedback-first penalty condition (feedback present, 95% HDI [2.92, 3.31]; feedback absent, 95% HDI [2.26, 2.58]; Fig. 7, left bottom panel) condition and feedback-second neutral condition (feedback present, 95% HDI [2.80, 3.14]; feedback absent, 95% HDI [2.35, 2.77]; Fig. 7, right top panel) condition. When the target prevalence was regular, the same pattern also applied to the participants who received feedback first in the penalty condition (feedback present, 95% HDI [3.11, 3.52]; feedback absent, 95% HDI [2.48, 2.93]; Fig. 7, left top panel).

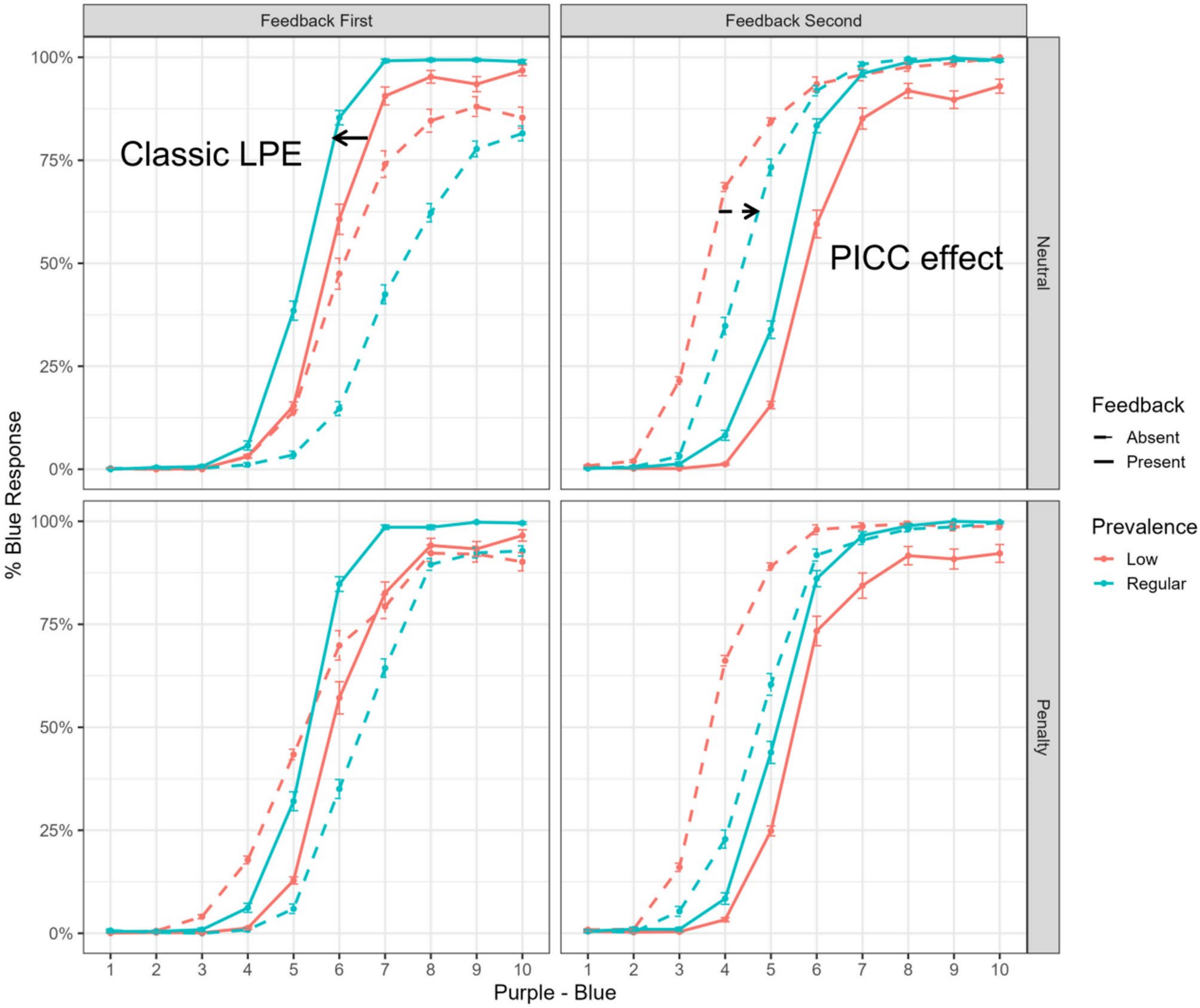

Fig. 5. The percentage of blue responses in Experiment 2 as a function of the binned category (explained in the text), target prevalence, and feedback display (absent: dotted line, present: solid line) for the feedback-first and feedback-second groups varied by the two different reward schemes (neutral and penalty payoffs).

Discussion

Experiment 2 randomly assigned participants to either the penalty or neutral reward schemes. Consistent with our hypothesis, our findings suggested that the penalty led to an increase in "target-present" responses, indicating more liberal criteria. However, this finding was evident only when the participants were assigned to the feedback-first condition and did not receive feedback (i.e., the second phase of the experiment). This finding indicates that rewards have a considerably limited impact in this rewarded context. Our data suggested that the penalty did not diminish the criteria gap between the two prevalence situations. Instead, the penalty led to a much larger change in the criteria without feedback (i.e., PICC) compared with the change in the neutral condition.

In addition to the influence of reward schemes, our results reproduced PICC and the LPE, as in Experiment 1. We observed a consistent trend of criterion shifts, which were influenced by whether feedback was present. Our findings also indicated that the sequence in which feedback was presented had a significant impact. When trial-by-trial feedback was absent, participants who had no prior experience with feedback (feedback-second condition) were more inclined to have liberal criteria than were those participants for whom feedback was removed (feedback-first condition), regardless of their assigned reward schemes.

General discussion

Many critical real-world decisions involve significant economic and safety risks. Decision-makers often face the uncertainty of severe consequences, such as lawsuits or catastrophic accidents, which can loom over them like the Sword of Damocles as they make these decisions. Previous research has shown that the presence or absence of feedback can lead to different patterns of criterion shifts in perceptual decision-making in response

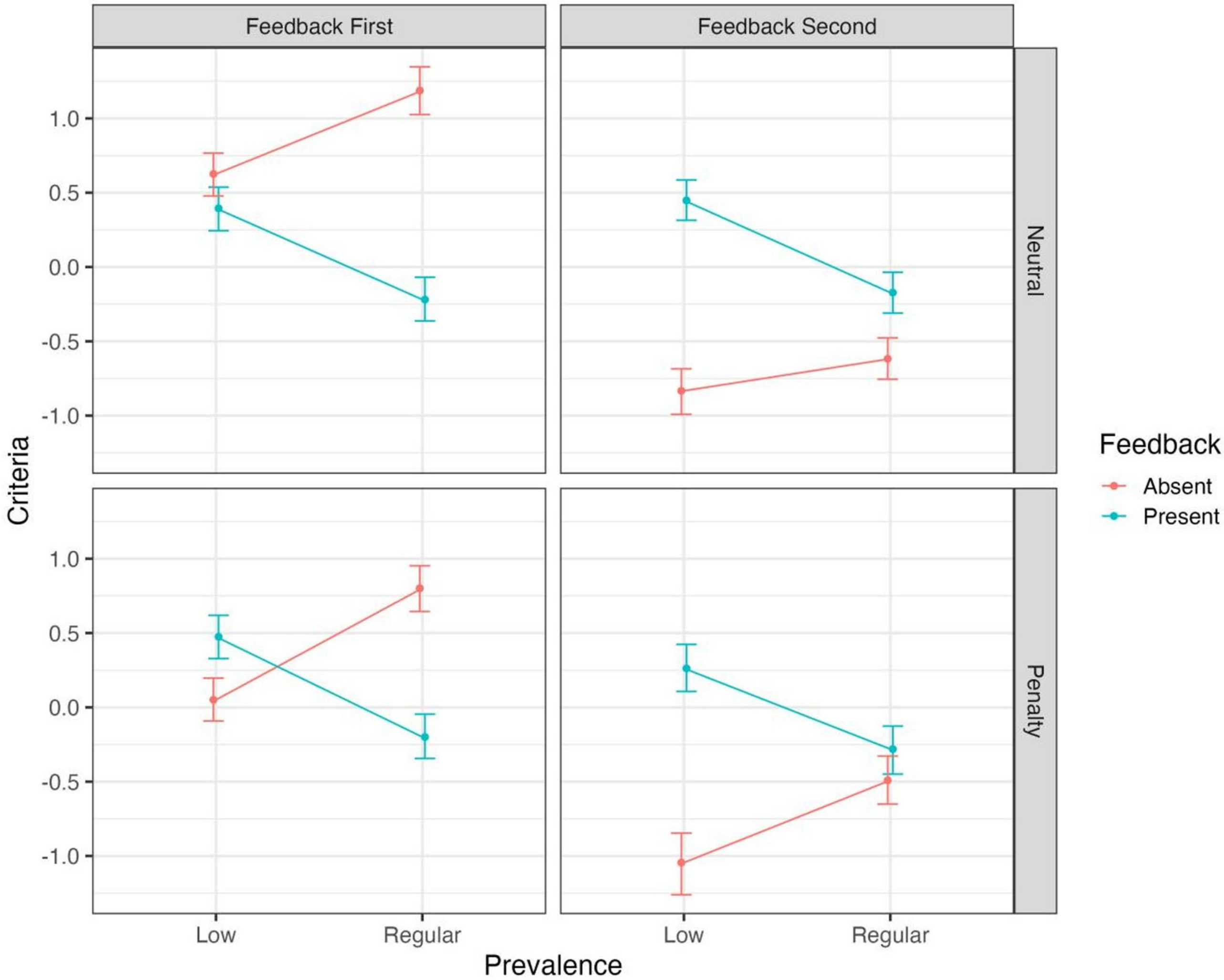

Fig. 6. The 95% HDI of the posterior distribution (median in dots) of the group-level criteria in Experiment 2.

	Feedback first		Feedback second	
Feedback	Present	Absent	Present	Absent
Reward				
Neutral	[– 0.82, – 0.41]	[0.34, 0.78]	[– 0.71, – 0.43]	[0.01, 0.42]
Penalty	[– 0.88, – 0.47]	[0.54, 0.96]	[– 0.77, – 0.31]	[0.29, 0.82]

Table 4. Criterion shift (credible mean differences) as a function of manipulative conditions in experiment 2.

to changes in target prevalence. Building on this, the present study examined whether criterion shifts could also be affected by the rewards associated with decisions. Our results indicated that although the influence of rewards was limited to specific contexts, the sequence in which feedback on rewards and accuracy was presented had a notable impact on biasing participants' perceptual decision-making.

In the first experiment, we designed the targets in regular- and low-prevalence conditions to carry equal expected values. However, we found no evidence that the participants adjusted their decision criteria to align with this reward scheme. In the second experiment, we altered the payoff matrix to introduce substantial penalties for missed errors, aiming to induce shifts in criteria that were not solely dependent on prevalence. The results of this second experiment indicated that changes in reward schemes influenced the decision-making process, but this effect was observed only when participants operated without feedback following experiences with feedback.

One notable finding from our previous study[15] was that novices exhibited a reversed criterion shift trend resembling that of PICC. While we originally hypothesized that this phenomenon could be explained by the effect of a lack of feedback, we also considered that novices' expectations of payoffs from their decisions might significantly influence this shift. In contrast, we found no evidence that equalizing the expected value or

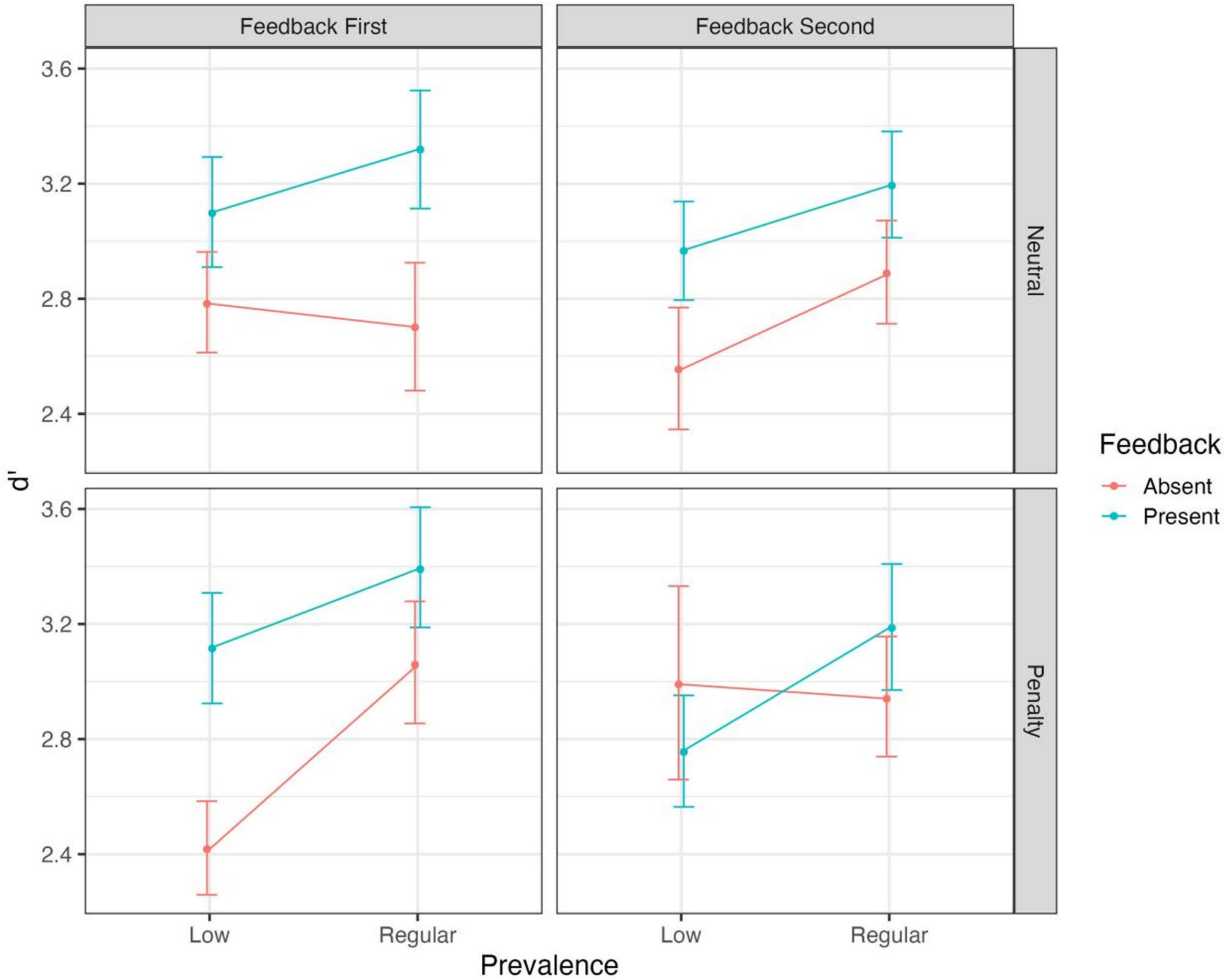

Fig. 7. The 95% HDI of the posterior distribution (median in dots) of the group level d' in Experiment 2.

penalties for incorrect responses impacted PICC or the LPE or caused the shift to reverse. The findings suggest that the more liberal criteria adopted by novices might not be attributable to their exposure to specific reward expectations. Given that no feedback was provided to either the expert or novice groups during the tasks in[15], we propose that our previous observed discrepancy in criterion shifts may be due to the different cognitive processing strategies used in expert diagnosis[23,24], which requires further exploration in future studies.

Navalpakkam discovered that observers in visual search tasks quickly learned the optimal decision criterion to maximize expected rewards[16]. Similarly, our earlier research[8] revealed that introducing penalties for incorrect responses significantly increased participants' likelihood of giving "target-present" responses. However, a novel observation from our current research indicates that reward schemes have a more limited effect on perceptual categorization tasks than on visual search tasks. In Experiment 2, participants in the neutral payoff condition displayed only moderate changes in their decision criteria when initially performing the task without feedback, as opposed to when feedback was introduced first. This difference was probably due to the fact that the evaluated payoffs were compared to a psychological benchmark, such as one's 'status quo'[17]: The neutral payoff condition rewarded correct responses with 1 point and penalized erroneous responses by 50 points. In a competitive setting, participants may exhibit loss aversion, leading them to provide more "target-present" responses even when the target prevalence shifts from regular to low. This tendency is particularly evident when rewards are based on cumulative points across blocks rather than updated trial-by-trial feedback. However, this conclusion relies on the explicit assumption that all participants share a similar level of risk aversion. Future research should directly examine individual differences in risk aversion to further validate this finding.

Unlike previous visual search tasks[8,16], in which the proposed criterion shift induced by payoffs could be attributed to the quitting threshold (e.g., more search time), more liberal criteria (e.g., expanded categorical concepts in individual item decisions), or both based on the dual-threshold model[11], we employed a color categorization task where there were no uninspected items associated with the quitting threshold. Therefore, our future study plans to apply models such as the drift diffusion model[25] to further elucidate how various elements—such as behavioral thresholds or decision-making strategies—impact the observed criterion shift due to prevalence changes in reward-influenced categorization tasks.

Despite its critical role in perceptual learning, feedback has been infrequently integrated into tasks examining the prevalence effect[3,6,15,26,27]. In line with earlier research on how feedback influences the prevalence effect[13], one of our earlier studies also demonstrated that participants with explicit knowledge about prevalence responded differently than those who had learned about it through experience did[8]. Specifically, in low-prevalence conditions, trial-by-trial feedback resulted in a higher frequency of "target-present" responses. In the present research, we further argue that the presentation and sequence of feedback significantly influenced the criteria adopted by the participants. For example, removing trial-by-trial feedback may lead to more liberal responses, particularly when the goal is to encourage "target-present" responses. The evidence suggests that the history of receiving feedback adaptively shapes decision-makers' choices[28,29]. Since our task involved only a competitive context[8,16], future experimental designs should incorporate both feedback and trial-by-trial payoffs to better model decision-making behaviors[30,31].

In line with previous research suggesting that the LPE is difficult to mitigate[3], our findings further demonstrate that both the sequence of feedback presentation and reward schemes have a minimal influence on the LPE. However, in the absence of feedback, multiple factors can shape the results associated with PICC. Specifically, our study highlights the importance of the order in which feedback is provided. This observation was partially addressed in prior work by Wolfe and colleagues[3,5], who aimed to mitigate the LPE by suggesting that feedback can provide additional information about target probability. Their findings showed that participants who received feedback during high-prevalence trials, but not during low-prevalence trials, maintained the liberal criterion established during high-prevalence trials even when the prevalence decreased. Our research builds on these findings by offering explanatory mechanisms that account for this mitigation strategy. Consistent with recent research suggesting that reduced ambiguity can impact decision-making[32], our research indicated that participants who were initially exposed to feedback experienced a stronger and more lasting impact than did those who were not. Notably, individuals influenced by the predominant feedback effect were more likely to retain their conservative criterion even in the absence of feedback. These results underscore the importance of considering the sequence of feedback presentation when feedback is integrated into prevalence research. Although the display of feedback in real-world search scenarios may be practically constrained, incorporating it in training settings could effectively enhance trainee performance. Additionally, future research should investigate alternative feedback formats within the framework of prevalence search or classification tasks. This includes exploring aided decision-making systems[33] and the involvement of additional decision-makers[34,35].

Conclusion

In summary, our study explored the effects of reward schemes and feedback delivery on perceptual decisions influenced by target prevalence. Our findings highlighted that feedback not only altered the direction of prevalence-induced criterion shifts but also that the order of feedback presentation played a significant role. Participants who performed without immediate feedback displayed more liberal decision criteria than those who received prior feedback. Contrary to our initial hypothesis that strategic reward schemes would mitigate the disparities caused by prevalence-induced criterion shifts, our results indicate that the influence of reward schemes is relatively modest. This research contributes valuable insights that could enhance performance across varying conditions of target prevalence.

Data availability

All the data and analysis code have been made publicly available at the Open Science Framework (OSF) and can be accessed at https://osf.io/h85dv/.

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References

1. Wolfe, J. M., Horowitz, T. S. & Kenner, N. M. Rare items often missed in visual searches. *Nature* **435**, 439–440 (2005).
2. Horowitz, T. S. Prevalence in visual search: from the clinic to the lab and back again. *Jpn Psychol. Res.* **59**, 65–108 (2017).
3. Wolfe, J. M. et al. Low target prevalence is a stubborn source of errors in visual search tasks. *J. Exp. Psychol. Gen.* **136**, 623–638 (2007).
4. Nakashima, R. et al. The effect of expert knowledge on medical search: medical experts have specialized abilities for detecting serious lesions. *Psychol. Res.* **79**, 729–738 (2014).
5. Wolfe, J. M., Brunelli, D. N., Rubinstein, J. & Horowitz, T. S. Prevalence effects in newly trained airport checkpoint screeners: trained observers miss rare targets, too. *J. Vis.* **13**, 33–33 (2013).
6. Lau, J. S. H. & Huang, L. The prevalence effect is determined by past experience, not future prospects. *Vis. Res.* **50**, 1469–1474 (2010).
7. Peltier, C. & Becker, M. W. Decision processes in visual search as a function of target prevalence. *J. Exp. Psychol. Hum. Percept. Perform.* **42**, 1466–1476 (2016).
8. Zhang, H. & Houpt, J. W. Exaggerated prevalence effect with the explicit prevalence information: the description-experience gap in visual search. *Atten. Percept. Psychophys.* **82**, 3340–3356 (2020).
9. Evans, K. K., Birdwell, R. L. & Wolfe, J. M. If you don't find it often, you often don't find it: why some cancers are missed in breast Cancer screening. *Plos One.* **8**, e64366 (2013).
10. Green, D. M. & Swets, J. A. *Signal Detection Theory and Psychophysics*. (1966).
11. Wolfe, J. M. & Van Wert, M. J. Varying target prevalence reveals two dissociable decision criteria in visual search. *Curr. Biol.* **20**, 121–124 (2010).
12. Levari, D. E. et al. Prevalence-induced concept change in human judgment. *Science* **360**, 1465–1467 (2018).

13. Lyu, W., Levari, D. E., Nartker, M. S., Little, D. S. & Wolfe, J. M. Feedback moderates the effect of prevalence on perceptual decisions. *Psychon Bull. Rev.* **28**, 1906–1914 (2021).
14. Nakashima, R., Kobayashi, K., Maeda, E., Yoshikawa, T. & Yokosawa, K. Visual search of experts in medical image reading: the effect of training, target prevalence, and expert knowledge. *Front Psychol* **4**, (2013).
15. Zhang, H. et al. Hip fracture or not? The reversed prevalence effect among non-experts' diagnosis. *Cogn Res. Princ Implic* **8**, (2023).
16. Navalpakkam, V., Koch, C. & Perona, P. Homo economicus in visual search. *J. Vis.* **8**, 548–548 (2010).
17. Johnson, J. G. & Busemeyer, J. R. Decision making under risk and uncertainty. *Wiley Interdiscip Rev. Cogn. Sci.* **1**, 736–749 (2010).
18. Peirce, J. et al. PsychoPy2: experiments in behavior made easy. *Behav. Res. Methods.* **51**, 195–203 (2019).
19. Paulewicz, B. & Blaut, A. The Bhsdtr package: a general-purpose method of bayesian inference for signal detection theory models. *Behav. Res.* **52**, 2122–2141 (2020).
20. Kruschke, J. K. Doing Bayesian Data Analysis: A Tutorial with R, JAGS, and Stan. (2014).
21. Meredith, M., Kruschke, J. & HDInterval Highest (Posterior) density intervals. (2016). https://doi.org/10.32614/cran.package.hdinterval.
22. Cornwall, A. C., Davis, T., Byrne, K. A. & Worthy, D. A. Effects of categorical and numerical feedback on category learning. *Cognition* **225**, 105163 (2022).
23. Kundel, H. L., Nodine, C. F., Conant, E. F. & Weinstein, S. P. Holistic component of image perception in mammogram interpretation: Gaze-tracking study. *Radiology* **242**, 396–402 (2007).
24. Kundel, H. L., Nodine, C. F., Krupinski, E. A. & Mello-Thoms, C. Using Gaze-tracking data and mixture distribution analysis to support a holistic model for the detection of cancers on mammograms. *Acad. Radiol.* **15**, 881–886 (2008).
25. Ratcliff, R. & McKoon, G. The diffusion decision model: theory and data for Two-Choice decision tasks. *Neural Comput.* **20**, 873–922 (2008).
26. Chen, W., HolcDorf, D., McCusker, M. W., Gaillard, F. & Howe, P. D. L. Perceptual training to improve hip fracture identification in conventional radiographs. *Plos One*. **12**, e0189192 (2017).
27. Schwark, J., Sandry, J., MacDonald, J. & Dolgov, I. False feedback increases detection of low-prevalence targets in visual search. *Atten. Percept. Psychophys*. **74**, 1583–1589 (2012).
28. Anderson, B. A. et al. The past, present, and future of selection history. *Neurosci. Biobehav Rev.* **130**, 326–350 (2021).
29. Awh, E., Belopolsky, A. V. & Theeuwes, J. Top-down versus bottom-up attentional control: a failed theoretical dichotomy. *Trends Cogn. Sci.* **16**, 437–443 (2012).
30. Konstantinidis, E., Harman, J. L. & Gonzalez, C. Patterns of choice adaptation in dynamic risky environments. *Mem. Cognit*. **50**, 864–881 (2022).
31. McCormick, E. N., Cheyette, S. J. & Gonzalez, C. Choice adaptation to changing environments: trends, feedback, and observability of change. *Mem. Cognit*. **50**, 1486–1512 (2022).
32. Puntiroli, M., Kandul, S., Bezençon, V. & Lanz, B. Seeing through the fog: the ability to resolve ambiguity reduces dishonesty. *Pers. Soc. Psychol. Bull.* https://doi.org/10.1177/01461672241305687 (2025).
33. Boskemper, M. M., Bartlett, M. L. & McCarley, J. S. Measuring the efficiency of Automation-Aided performance in a simulated baggage screening task. *Hum. Factors*. **64**, 945–961 (2021).
34. Enright, A. & McCarley, J. S. Collaborative search in a mock baggage screening task. *J. Exp. Psychol. Appl.* **25**, 716–732 (2019).
35. Zhang, H., Zhu, P. F. & Yang, C. T. Group efficiency based on the termination rule in the multiple-targets visual search task. *Psychon Bull. Rev.* https://doi.org/10.3758/s13423-024-02558-5 (2024).

Author contributions
HZ and CY conceived the experimental design. HZ, JZ, and YC programmed the experiments. JZ and YC collected the data. JZ and HZ performed the data analysis and prepared the initial manuscript. HZ and CY revised the manuscript. All the authors read and approved the final manuscript.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
The study was approved by the Institutional Review Board at Central China Normal University (protocol code: CCNU-IRB-20240325 A) and the Human Research Ethics Committee of Taipei Medical University (protocol code: TMU-IRB-N202202034) for Experiments 1 and 2, respectively.

Additional information
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