Effect of Feedback Mode and Task Difficulty on Quality of Timing Decisions in a Zero-Sum Game

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What is This?
Objective: The objective was to investigate the interaction between the mode of performance outcome feedback and task difficulty on timing decisions (i.e., when to act).

Background: Feedback is widely acknowledged to affect task performance. However, the extent to which feedback display mode and its impact on timing decisions is moderated by task difficulty remains largely unknown.

Method: Participants repeatedly engaged a zero-sum game involving silent duels with a computerized opponent and were given visual performance feedback after each engagement. They were sequentially tested on three different levels of task difficulty (low, intermediate, and high) in counterbalanced order. Half received relatively simple “inside view” binary outcome feedback, and the other half received complex “outside view” hit rate probability feedback. The key dependent variables were response time (i.e., time taken to make a decision) and survival outcome.

Results: When task difficulty was low to moderate, participants were more likely to learn and perform better from hit rate probability feedback than binary outcome feedback. However, better performance with hit rate feedback exacted a higher cognitive cost manifested by higher decision response time.

Conclusion: The beneficial effect of hit rate probability feedback on timing decisions is partially moderated by task difficulty.

Application: Performance feedback mode should be judiciously chosen in relation to task difficulty for optimal performance in tasks involving timing decisions.

Keywords: gaming, uncertainty, probability, outcome, display

INTRODUCTION
Timing decisions are a subclass of decisions where the critical factor is not what action to take but rather when to take action (see Kahan & Rapoport, 1974). Whereas timing decisions have been subjected to extensive mathematical modeling in the context of game theory (Rapoport, Kahan, & Stein, 1976), little work has focused on factors that can improve timing decisions in applied settings. Timing decisions in applied domains can occur at various time scales. However, the principle of optimizing when to initiate an action applies irrespective of the time scale in the timing decision. For instance, in medical practice, the decision of when to initiate an action over a long time scale (e.g., a treatment plan) can greatly affect the success or failure of an intervention (e.g., Braithwaite et al., 2008). Similarly, timing decisions on short time scales play a key role in many fast-paced competitive interactions that, for example, are characteristic of most sports. More critically, timing decisions on short time scales can also make the difference between life and death in military maneuvers, where compromise between rapid fire and engagement accuracy poses an endemic trade-off. In the present research, we investigated the effect of outcome feedback and task difficulty on short time scale timing decisions in a zero-sum game of military relevance.

Outcome Feedback, Task Difficulty, and Performance
Most early studies of outcome feedback focused on whether its presence or absence led to improved learning and performance (for a review, see Richardson, 1991). More recently, research has examined the effect of specific features of the feedback itself (e.g., strength, frequency, display mode) on learning and performance. Such work indicates that benefits of
feedback are contingent on the goodness of fit between features of the feedback and individual task, and contextual variables (e.g., Lurie & Swaminathan, 2009). Of particular relevance to the present research, a meta-analysis of approximately 3,000 papers showed that task difficulty moderated the impact of feedback on performance (Kluger & DeNesi, 1996). Simple task performance benefitted from feedback more than did difficult task performance. This may be because participants are better able to infer the processes underlying outcome feedback when the task is simpler and, accordingly, they may be better able to adjust their performance (Balzer, Doherty, & O’Conner, 1989).

The present research extends previous literature on feedback and performance in two ways. First, although much is known about the interactive effect of feedback and task difficulty on a wide assortment of performance measures (Kluger & DeNesi, 1996), the extent to which task difficulty and feedback influence timing decisions remains largely unknown. Second, whereas the previous feedback literature has focused on a host of manipulations including the presence or absence of feedback (Camerer, 1997; Camerer & Ho, 1999; Weber, 2003), feedback strength (Hogarth, Gibbs, McKenzie, & Marquis, 1991), feedback delay (Sterman, 1989), noisiness of feedback (March, 1999), and exactingness and incentives (Hogarth et al., 1991), little is known about how the mode of presenting feedback influences subsequent decision making (Lurie & Swaminathan, 2009).

We addressed this gap by manipulating the presentation of feedback information using binary and hit rate probability feedback modes in the context of a novel paradigm called Dueler’s Dilemma (described in detail later), which allowed for the difficulty of the decision-making environment to be precisely manipulated. Briefly, participants were required to decide when to shoot an unseen opponent in a simulated silent shooting duel and were given outcome feedback at the end of each engagement in either a binary outcome or hit rate probability mode. The binary feedback revealed to the participant using silhouette images whether the participant was alive or dead. The hit rate feedback depicted in a bar chart with two bars the probabilities of the participant and opponent being killed. The latter was more informative because it provided the participant with distributional information, but it was also more difficult to interpret due to the probabilistic nature of the feedback. That is, unlike participants who received binary feedback, those receiving hit rate feedback did not learn the specific outcome of any duel. Engagement trials were counterbalanced in three scenarios that varied in terms of task difficulty (viz., low, intermediate, and high difficulty). Difficulty was defined in terms of statistical properties of the task environment (described in detail later), which directly affected the discriminability of optimal shooting times where the participant had a survival advantage over the opponent.

Hypotheses

An intuitive hypothesis is that participants would benefit more from the hit rate feedback than from the binary feedback because the former provides distributional information on the quality of the participant’s timing decision, whereas the latter provides only a single outcome of the duel. The normative importance of integrating distributional or statistical information in arriving at judgments and decisions is well known, as is the tendency for people to often underutilize or even neglect such information (Kahneman, Slovic, & Tversky, 1982). People often adopt an “inside view,” attending to characteristics of the case under consideration, while disregarding the blander “outside view” provided by relevant distributional information, often to the detriment of mitigating relative risk (Kahneman & Lovallo, 1993). Indeed, even when statistical information is used, it is often used incorrectly. For example, people often confuse diagnostic probabilities with the “inverse” posterior probabilities they are asked to estimate (Dawes, Mirels, Gold, & Donahue, 1993; Villejoubert & Mandel, 2002). Moreover, even statistical properties of chance processes are often mentally represented as concrete outcomes of a specific case (Mandel, 2008). Thus, although hit rate feedback is theoretically more informative, it is unclear whether people can in fact benefit more from the distributional format.
Building on prior research showing that the effect of feedback on performance is moderated by task difficulty (Kluger & DeNesi, 1996), we tested a competing hypothesis that any observed advantage of hit rate feedback over binary feedback would be maximized under conditions of low task difficulty and possibly eliminated under high task difficulty, where the participant would be more cognitively taxed by the low discrimination environment. Specifically, we predicted that the benefit of hit rate feedback over binary feedback would be evident in the form of higher survival probabilities under low difficulty, but that the advantage would be attenuated as difficulty increased. We also predicted that decision response time (RT) would be higher with hit rate feedback condition than with binary feedback when the task was difficult, and that the RT difference would be attenuated as difficulty declined. The latter prediction reflects the fact that additional effort is required of people to interpret probabilistic and numerical information (Gigerenzer & Edwards, 2003; Lipkus & Hollands, 1999; Visschers, Meertens, Passchier, & de Vries, 2009). Thus, when participants are already cognitively taxed by the task demands, the more complex hit rate feedback will provide an additional burden on the participants’ cognitive resources.

A secondary aim of the research was to examine whether performance would be influenced by instructing participants to adopt either a defensive or offensive engagement posture. Within a military context, engagement posture is shaped by the commander’s intent, which, if effective, becomes the soldier’s shared intent (Pigeau & McCann, 2000). Given that our research participants were military members with rifle training, we were interested in exploring whether task instructions (as a proxy for the commander’s intent) to assume a defensive or offensive posture would affect the quality of their time-to-shoot decisions. In a defensive posture, the primary goal is to stay alive, whereas the primary goal in an offensive posture is to acquire the target (i.e., kill the opponent). Although these goals are correlated, the optimal shooting times for each of them varied to differing degrees across levels of task difficulty. Specifically, the optimal shooting time did not differ by posture in the low difficulty condition. However, with intermediate task difficulty, optimal shooting times for the defensive and offensive postures differed, and that difference was even greater in the high difficulty condition. We tested the hypothesis that the participants’ probability of survival would be greater in the defensive condition, whereas their probability of acquiring the target would be greater in the offensive condition.

METHOD

Participants

A total of 130 active military personnel of the Canadian Armed Forces volunteered to participate in this experiment. The sample had a mean age of 27 years (SD = 10) and mean military service length of 5 years (SD = 8) and was 97% male. All participants had successfully completed rifle training.

Design

Participants were randomly assigned to conditions in a 2 (posture: defensive, offensive) × 2 (feedback: binary, hit rate) × 3 (difficulty: low, intermediate, high) mixed factorial design. Posture and feedback were manipulated between subjects, whereas difficulty was manipulated within subjects.

Procedure

Participants completed the experiment individually at a computer workstation. All participants were instructed to read the following general introductory paragraph:

Shots fired by you or at you have a linearly increasing chance of hitting from 0% at time 0 to 100% at time 100. You will choose your shooting time by moving the cursor on the 0 to 100 time scale and clicking your desired time. The probability that you or your opponent is hit depends on the combination of shooting times that you and your opponent choose (e.g., if your opponent shoots first, your only chance of hitting your opponent depends on whether you are hit). Firing earlier than your opponent does not disrupt their shooting accuracy. The shooting times chosen by your opponent can vary.
and are concealed from you. Hence, the probability of being hit changes with each engagement, even if you choose to shoot at the same time as in a previous engagement. However, patterns will emerge with a sufficient number of engagements.

Next, participants were introduced to the feedback mode they would receive throughout the experiment. In the binary condition, participants were told that after each engagement, two figures would be shown indicating the outcome of the engagement. They were shown a screen shot of the feedback, as illustrated in Figure 1a. They were further told,

The blue figure on the left shows whether you survived (standing) or were hit (laying down), and the red figure on the right shows the same for your opponent. Both figures will either be up (i.e., neither hit) or one figure will be up and the other will be down; both figures will never be down at the same time.

Participants in the hit rate condition were told that, after each engagement, two vertical bars would be shown as illustrated in Figure 1b. They were further told, “The blue bar on the left shows the probability that you have been hit and the red bar on the right shows the probability that you hit your opponent.”

After explaining to participants the nature of the feedback they would receive, the posture manipulation was introduced. All participants read, “Please imagine the following scenario as you complete your task. You are engaged in an operation where CF troops have sustained many casualties.” Then, in the defensive condition, participants read,

The Government of Canada is under political pressure to withdraw troops and end the mission. Given the situation, your commander has placed top priority on ensuring your own survival. Thus, you should attempt to shoot your opponent at a time that offers you the best chance of remaining alive after engaging your opponent.

In contrast, in the offensive condition, participants read,

The Government of Canada is under political pressure to effectively eliminate the threat or else end the mission. Given the situation, your commander has placed top priority on destroying the opponent. Thus, you should attempt to shoot your opponent at a time that offers you the best chance of killing him.

After receiving these instructions, participants completed 20 practice duels using task parameters that differed from the three scenarios used to define low, intermediate, and high difficulty conditions, which were run in blocks. The order of these blocks was fully counterbalanced across participants. In both the practical and experimental duels, participants selected their shooting times using a mouse-activated horizontal sliding bar (Figure 1c). No time limit was imposed on selecting the shooting time for each duel, but total test time was limited to 15 min per block, which included the fixed 5 s of feedback display time following each duel. Participants were notified when a block ended and initiated the next block within 1 to 2 min upon selecting the shooting time for the first duel. This ensured that the entire experiment was completed within 1 hr.

The two dependent variables were the participants’ scaled shooting time, $T_{\text{shoot,p}}$, and RT in ms. Although RT was of theoretical interest, $T_{\text{shoot,p}}$ was not. Rather, shooting times of the participant and opponent were used to calculate the participants’ probability of surviving the duel, $P_{\text{survives}}$, and the participants’ probability of acquiring the target, $P_{\text{kill}}$, both of which were of theoretical interest. We report descriptive statistics on $T_{\text{shoot,p}}$ in Figure 3, introduced in the next subsection, and we examine RT, $P_{\text{survive}}$, and $P_{\text{kill}}$ in hypothesis tests reported in the results section.

**Dueler’s Dilemma Task and Difficulty Manipulation**

Dueler’s Dilemma (Tikuisis & Keefe, 2007) is a zero-sum, two-contestant, single-fire, silent shooting game of timing with stochastic outcomes. The participant must decide the optimal
time to fire a single shot at an unseen computerized opponent to survive the duel and hit the opponent. This operationalized variant of the duel has been described by Presman and Sonin (2006), and it differs from the classic “noisy” version of a duel (Rapoport et al., 1976) in that neither contestant can witness (by sight or sound) when the opponent fires a shot nor see the outcome of both shots fired until the duel is completed.

The time-dependent probability of hitting a target (for both the participant and opponent) is a simple linear relationship to when a shot is fired, based on a dimensionless time scale ranging from 0 to 100 (e.g., 0%, 10%, 20% at scaled times of 0, 10, 20, etc.). However, because the participant is
not aware of when the opponent’s shot is fired, which is independent of the participant’s choice, the challenge lies in deciding when to commit fire—“when” in this context refers to $T_{\text{shoot},p}$ rather than $RT$. The inherent dilemma arises between delaying engagement sufficiently long to increase the probability of hitting the opponent, but not waiting too long to risk being hit by a shot taken earlier by the opponent.

Possible outcomes include the participant being hit and the opponent surviving, the opponent being hit and the participant surviving, or both the participant and the opponent surviving. In all cases, the net utility of the outcome is zero (−1 for being hit, +1 for hitting, and 0 for a tie), hence the zero-sum characterization of the game. Although there is a theoretical possibility that both the participant and opponent can be simultaneously hit (if both shoot at precisely the same time and both shots hit their targets), this outcome is virtually impossible and ignored since the opponent’s shooting time is generally a computer-generated multidigit decimal number, whereas the participant’s shooting time was limited to an integer.

Figure 2 provides an example of a possible duel and associated outcomes. In this example, the opponent’s shooting time, $T_{\text{shoot},o}$, is fixed at a scaled value of 75. If the participant shoots at $T_{\text{shoot},p} < 75$, then his or her chance of hitting the opponent becomes his or her shooting time expressed as a percentage, hence the dashed line that increases from 0% to 75%. If $T_{\text{shoot},p}$ exceeds 75, the probability that the participant is hit becomes 75%. If the opponent fails to hit the participant in this case (25% chance), then the probability that the participant’s shot hits the opponent becomes $T_{\text{shoot},p} \times (100 - 75)\%$. Up until the scaled time of 75, the probability of the participant having been hit by the end of the engagement decreases linearly from 75% to 18.75% due to the increasing probability that the opponent will be hit. The zone of advantage (ZOA) for the participant, defined by a higher average probability of hitting the opponent than of being hit, lies in the shaded region constrained by $42 < T_{\text{shoot},p} < 75$ in Figure 2. Formally derived equations that describe all possible duel outcomes are provided in the appendix.

In the experiment, $T_{\text{shoot},o}$ was not fixed. In the intermediate difficulty condition (Figure 3 middle graph), $T_{\text{shoot},o}$ was a uniform continuous random variable with a range of 0 to 100. In the low and high difficulty conditions (Figure 3, top and bottom graphs, respectively), the normal distribution function was used to randomly generate $T_{\text{shoot},o}$ about different mean shooting times with different variances, but truncated to the range of 0 to 100. Specifically, random numbers (from 0 to 1) were used in the Microsoft Excel function NORM.INV (random number, mean, SD) to generate $T_{\text{shoot},o}$ in these conditions. Values lower than 0 or higher than 100, which occurred in fewer than 0.0004% of the samplings in this study, were dismissed and resampled. By manipulating the task characteristics as just described, the level of difficulty corresponds to the size of ZOA such that decreased height (i.e., the separation of the probabilities of the participant and opponent being killed) and decreased width increase task difficulty.

**RESULTS**

**Preliminary Tests**

**Verification of difficulty manipulation.** The opponent’s shooting times were examined to confirm that their shooting characteristics matched what was programmed for each difficulty level. As expected by design, mean $T_{\text{shoot},o} = 90.0$ ($SD = 2.0$),
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50.0 (SD = 28.8), and 45.0 (SD = 10.0) for low, intermediate, and high difficulty conditions, respectively.

Trial variation and parsing for subsequent tests. All participants completed at least 63 duels per experimental condition. The percentage of participants who completed more duels across all conditions decreased to 97.7% (70 duels), 93.8% (80 duels), 85.4% (90 duels), and 66.2% (100 duels). Given these characteristics, each participant’s first 20 duels were compared to his or her last 20 duels within each level of difficulty to test performance change (i.e., change $[\Delta]$ in RT, $P_{\text{survive}}$, and $P_{\text{kill}}$). We also examined the last 20 duels in tests of factor effects once participants had sufficient opportunity for learning. (Data are available upon request to the authors.)

Task Experience

Response time. As task familiarity increased, RT was expected to decrease. Thus, we predicted that the difference in RT between the late (last 20) and early (first 20) duels would be negative overall. $\Delta$RT was examined as a function of posture, feedback, and difficulty in a mixed analysis of variance (ANOVA). Only the three-way interaction, plotted in Figure 4, was significant, $F(2, 125) = 4.43, p < .02, \eta^2 = .07$. As Figure 4 shows, $\Delta$RT was negative in all conditions except for the defensive posture + binary feedback + high difficulty condition, where there was virtually nil change. The interaction effect reveals a clear crossover interaction effect of difficulty and feedback in the defensive posture condition (top panel of Figure 4) that was not observed in the offensive posture condition (cf. bottom panel of Figure 4). The defensive interaction effect reflects the fact that the response speed increase from early to late duels accelerated as a function of task difficulty when participants received hit rate feedback and decelerated (effectively to zero) as a function of task difficulty when they received binary feedback.

Probability of survival. The change in survival probabilities, $\Delta P_{\text{survive}}$, was similarly examined as a function of posture, feedback, and difficulty in a mixed ANOVA. There was a very large and significant main effect of difficulty,
F(2, 125) = 91.49, p < .001, \eta^2 = .59, as well as a large and significant main effect of feedback, F(1, 126) = 52.15, p < .001, \eta^2 = .29. Difficulty and feedback significantly interacted, F(2, 125) = 35.54, p < .001, \eta^2 = .36, and no other effect in the model was significant. Figure 5, which plots the interaction effect, confirms the manipulation’s effectiveness shown by the main effect of difficulty. Performance increases decelerated with increasing levels of difficulty. It is also evident from Figure 5 that, on average, hit rate feedback benefited learning how to survive much better than binary feedback. The simple effects of feedback were significant at all levels of difficulty (ps < .03) with the qualification, however, that the relative benefit was reversed in the high difficulty condition. Clearly, the high difficulty task was not learnable by most participants in 15 min. These trends are also evident in the general migration of the participants’ shooting times, as illustrated in Figure 3. Binary feedback did not lead to a significant positive probability change (one-sample t < 1), and hit rate feedback actually resulted in significant negative learning (one-sample t = 4.03, p < .001).

**Probability of target acquisition.** A comparable three-way mixed ANOVA on \( \Delta P_{kill} \) revealed a large and significant main effect of difficulty, F(2, 125) = 12.00, p < .001, \eta^2 = .16. The improvement in \( P_{kill} \) was significantly greater in the low difficulty condition (\( M_{est} = 0.11, SE = \)
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Response time. We examined RT as a function of feedback, posture, and difficulty in a mixed ANOVA. There were significant main effects of feedback, $F(1, 126) = 5.52, p < .03$, $\eta_p^2 = .04$, and difficulty, $F(2, 125) = 6.04, p < .005$, $\eta_p^2 = .05$, and these factors significantly interacted, $F(2, 126) = 4.04, p < .03, \eta_p^2 = .03$. Figure 6 plots the interaction effect, visually showing that the simple effect of difficulty on RT was nonsignificant in the binary condition ($p > .85$), whereas it was significant in the hit rate condition—particularly the linear trend, linear $F(1, 58) = 13.72, p < .001, \eta_p^2 = .19$.

Probabilities of survival and target acquisition. The correlation between probabilities of survival and target acquisition predictably decreased from low difficulty ($r = .98, p < .001$) to intermediate difficulty ($r = .59, p < .001$) to high difficulty ($r = .21, p < .02$). This reflects the varying degrees of asymmetry between the two probability types across levels of difficulty, as depicted in Figure 3.

There was a significant negative correlation between RT and $P_{\text{survive}}$ at low ($r = -.24, p < .01$) and intermediate ($r = -.20, p < .03$) but not at high ($r = -.09, p > .30$) levels of task difficulty. Unsurprisingly, given the nearly perfect relation between $P_{\text{survive}}$ and $P_{\text{kill}}$ at low task difficulty, there was also a significant negative correlation between RT and $P_{\text{kill}}$ at the low difficulty level ($r = -.22, p < .02$). However, RT was not significantly correlated with $P_{\text{kill}}$ at intermediate ($r = -.12, p > .15$) or high ($r = -.05, p > .55$) difficulty levels. Thus, there were weak negative effects of RT on performance at low and, partially, at intermediate difficulty levels where spending more time deliberating on the best shooting time evidently impeded rather than facilitated performance.

We examined the effect of posture, feedback, and difficulty on $P_{\text{survive}}$ in a mixed ANOVA, as illustrated in the top panel of Figure 7. As predicted, there was a large and significant main effect of difficulty, $F(2, 125) = 33.71, p < .001, \eta_p^2 = .35$. This was due to an almost perfectly linear decrease in $P_{\text{survive}}$ as difficulty increased, linear $F(1, 126) = 64.08, p < .001, \eta_p^2 = .34$. There was also a much weaker but significant main effect of feedback, $F(1, 126) = 5.23, p < .03, \eta_p^2 = .04$. This was due to better performance in the hit rate condition. No other effect in the model was significant.

Although the feedback by difficulty interaction effect was nonsignificant, it is evident that the data offer at least some support for the hypothesis that the relative benefit of hit rate feedback over binary feedback is greater at lower levels of task difficulty. Thus, we tested the a priori prediction by directly comparing the simple effect of feedback across levels of task difficulty. As predicted, hit rate feedback had a benefit over binary feedback at low task difficulty, $F(1, 128) = 5.40, p < .03, \eta_p^2 = .04$. In contrast, the simple effects of feedback at intermediate and high task difficulty were nonsignificant ($ps > .20$).

We also conducted a comparable three-way mixed ANOVA on $P_{\text{kill}}$, as illustrated in the bottom panel of Figure 7. Once again, there was a strong
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and significant main effect of difficulty, $F(2, 125) = 266.34, p < .001, \eta^2_p = .81$. As well, there was a much smaller but significant main effect of feedback, revealing an advantage in the hit rate condition, $F(1, 126) = 6.60, p < .02, \eta^2_p = .05$. No other effect in the model was significant, and it is evident from Figure 7 (bottom panel) that there is no support for a moderated effect of feedback on the probability of target acquisition.

Likewise, it is evident from a comparison of the two panels in Figure 7 that the effect of difficulty on performance was greater on $P_{\text{kill}}$ than it was on $P_{\text{survive}}$. A $2 \times 3$ (probability $\times$ difficulty) repeated-measures ANOVA confirmed that the main effect of probability was significant and large, $F(1, 129) = 681.57, p < .001, \eta^2_p = .84$. The effect of difficulty on $P_{\text{survive}}$ and $P_{\text{kill}}$ has already been established. The present analysis, however, confirmed that the interaction effect was also significant, $F(2, 128) = 267.29, p < .001, \eta^2_p = .81$. In other words, the manipulation of difficulty has a stronger effect on the probability of target acquisition than on the probability of participant survival.

**DISCUSSION**

It is well known that people have a tendency to adopt an “inside view” perspective when judging and deciding (Kahneman & Lovallo, 1993). This preference likely has both affective and cognitive determinants. An example of “inside view” bias that is likely to be affectively influenced is the finding that people are often more moved by a tangible example of human suffering than by the dry statistics of people killed in acts of collective violence (Slovic, 2007). A forecasting example that appears more likely due to cognitive processes is the finding that people will disregard valuable “outside view” base rate information in favor of an inside representative heuristic such as the personality sketch in the “lawyer–engineer” problem, even if the case-specific information is utterly nondiagnostic (Kahneman & Tversky, 1973; Tversky & Kahneman, 1982). This raises the question of whether people benefit from distributional feedback even when it offers a clear normative advantage over case-specific outcome feedback. Bearing in mind both the normative advantages and descriptive research on judgment.
and decision making, we sought to test which mode of feedback, if any, provided a performance advantage in a zero-sum game where decisions about the optimal time to shoot an opponent must be made.

The findings showed that, in spite of the penchant for the inside view, participants learned to survive in silent duels much more effectively from the distributional hit rate feedback than from the case-specific binary outcome feedback. This was evident at low and intermediate difficulty levels of the task, where there was in fact evidence that learning had occurred from early to late duels. Although there was no advantage for hit rate feedback at the high difficulty level, the findings indicate that that particular version of the task might have been too difficult to learn in the time allotted. However, even with that reversal at high difficulty, the statistical effect size was large. Thus, where the task was learnable, distributional feedback on hit rates offers a distinct advantage over case-specific feedback in terms of helping participants learn how to improve their probability of survival.

As well, the findings showed that hit rate feedback benefitted both survival and target acquisition more than binary feedback in late duels. Although there was some evidence that the size of the advantage of distributional over case-specific feedback in terms of survival probability was inversely related to task difficulty, the interaction in fact did not approach conventional levels of significance. Moreover, there was no evidence of such an interaction on the probability of acquiring the target. Thus, the present research offers only limited support for the notion that the effect of feedback on key performance measures would be moderated by task difficulty (cf. Kluger & DeNesi, 1996). As well, the effect sizes for the feedback main effects were small, and much smaller than the effect on learning how to improve one’s probability of survival noted earlier. This indicates that the advantage of distributional information is mainly seen on learning how to better survive, whereas the performance advantage close to the end of the task sequence was much more modest. The smaller effect sizes seen in late trial analyses are to be expected given that learning had occurred. At the limit—namely, had participants learned the optimal shooting times in each task—there would in fact be no need for any further feedback. In other words, learning should attenuate performance differences as a function of feedback mode.

Although distributional feedback offered a performance advantage over case-specific feedback, the former also had an associated time-saving cost, which increased with task difficulty. This result should serve to underscore the importance of not overgeneralizing the conclusions of this research. That is, in the present zero-sum dueling game, there was no penalty for how slowly or quickly the shooting time decision was made, but clearly there are many other situations where performance measures are strongly contingent on RT. Future research could modify the task structure to reward both a rapid RT and high survivability.

Future research could also seek to resolve the causal basis of the time-saving cost just noted. Its increase as a function of task difficulty indicates that processing such information is cognitively effortful. We propose that when participants are presented with an easy learning environment, the additional effort required to process the distributional hit rate feedback may add little burden to the working memory system. However, if that system is highly taxed, additional processing costs are not easily absorbed and more time is required to reach a decision. Future research could provide additional tests of this account. For instance, if the proposed account is correct, time-saving costs for distributional feedback as a function of task difficulty should exhibit a steeper increase for participants with low working memory capacity than for participants with high working memory capacity. Such capacity differences could be tested with the n-back test (Kirchner, 1958).

Likewise, it would be of value in future research to examine how individuals varying in numeracy processed these different types of graphical feedback. Objective numeracy refers to one’s ability to process numerical information, and statistical numeracy is a type of objective numeracy pertaining to the ability to process statistical information effectively (Cokely, Galesic, Schulz, Ghazal, & Garcia-Retamero, 2012). Unsurprisingly, individuals low in statistical numeracy have difficulty processing risk-related information (Peters, 2012; Reyna, Nelson, Han, & Dieckmann, 2009). Subjective numeracy, in contrast, refers to one’s preference for numeric
and quantitative graphical information over non-quantitative sources of information (Fagerlin et al., 2007). Hess, Visschers, Siegrist, and Keller (2011) found that, compared to participants with high subjective numeracy, those with low subjective numeracy had poorer comprehension of probability graphs and took longer to process graphical information (see also Hess, Visschers, & Siegrist, 2011). Based on previous research, one might expect that numeracy would be inversely related to time-savings costs associated with distributional feedback and directly related to performance increases (when compared to performance based on case-specific feedback).

A surprising result in this research was that there was no effect of feedback on offensive learning—namely, feedback had no effect on ΔPkill. This contrasts with the strong main effect of feedback on defensive learning and its interaction with task difficulty, as already discussed. A possible explanation is that hit rate feedback was less conducive to offensive learning than to defensive learning. The data confirm this: A 2 (probability change type) × 3 (difficulty) repeated measures ANOVA conducted on data from the hit rate condition showed a significant main effect of probability change type (F = 32.84, p < .001) and a significant interaction effect (F = 51.98, p < .001). Hit rate feedback had a stronger effect on defensive learning (Mdiff = 0.14, SE = 0.01) than on offensive learning (Mdiff = 0.07, SE = 0.01), an effect that was especially pronounced at the lowest level of task difficulty (Mdiff = 0.11 for offensive learning vs. 0.35 for defensive learning). Future research could examine the basis for the differential learning effect just described. One possibility is that participants attend more to hit rate information about themselves than about their opponent. This could be verified using eye tracking, as has been used in other research to examine graphical processing (e.g., Carpenter & Shah, 1998; Hess, Visschers, Siegrist, et al., 2011).

Finally, the findings did not reveal sensitivity to instructions that prioritized either one’s own survival (defensive posture) or target acquisition (offensive posture). The only significant effect involving posture was an unexpected three-way interaction effect on RT change—an effect about which we refrain from making speculative comments. That we found no effect of posture is surprising, given that our participants were professional soldiers who would not be unfamiliar with the notions of troop protection and adversarial target acquisition, which the instructional variation addressed. It may be that in the context of a fast-paced, multitrial task, such as Dueler’s Dilemma, the details of the instructions become quickly forgotten. This, however, would raise questions of how well troops can continue to attend to such instructions that are communicated by their commanders while actively serving on missions. It is possible that the present experiment was too difficult for the purpose of testing the effect of posture on performance. Recall that the low difficulty condition had identical optimal shooting times for defensive and offensive objectives. It would thus be advantageous to test the effect of posture on a less complex task where the distance between defensive and offensive optima was systematically varied.

**APPENDIX**

Herein all scaled shooting times are abbreviated for readability such that Tshoot,p becomes Tp and Tshoot,o becomes To, and shooting times are expressed from 0 to 1 to conform as probabilities.

### Mathematical Description of Task (Dueler’s Dilemma) Hit Probabilities (prob)

Hit probabilities when opponent shoots at a specific time, To:

\[
\text{Prob of participant being hit} = \begin{cases} 
T_o & \text{if } T_o < T_p \\
(1 - T_o) \cdot T_o & \text{if } T_o \geq T_p
\end{cases}
\]

and

\[
\text{Prob of opponent being hit} = \begin{cases} 
(1 - T_o) \cdot T_p & \text{if } T_o < T_p \\
T_o & \text{if } T_o \geq T_p
\end{cases}
\]

Mean hit probabilities when opponent shoots at random times between 0 and 1:

\[
\text{Mean prob of participant being hit} = \frac{1}{\frac{1}{2} T_p \cdot dT_o} + \frac{1}{\frac{1}{2} (1 - T_p) \cdot T_o \cdot dT_o} \\
= \frac{T_p^2}{2} + (1 - T_p) \left( \frac{1}{2} \cdot \frac{T_o^2}{2} \right) \\
= \frac{1}{2} \cdot \left( 1 - T_p + T_p^3 \right)
\]
and

\[
\text{Mean prob of opponent being hit } = \int_{T_o}^{T_p} (1 - T_o) \cdot T_p \cdot dT_o + \int_{T_o}^{T_p} T_p \cdot dT_o = T_p \left( T_p - \frac{T_p^2}{2} \right) + T_p \cdot (1 - T_p) = T_p \left( \frac{T_p^3}{2} \right)
\]

Mean hit probabilities when opponent shoots at normally distributed times about a mean value (\(\mu\)) with a specific standard deviation (\(\sigma\)), but truncated to the limits of 0 and 1:

\[
\text{Mean prob of participant being hit } = \int_{T_o}^{T_p} f(T_o) \cdot (1 - T_o) \cdot T_p \cdot dT_o + \int_{T_o}^{T_p} T_p \cdot dT_o = T_p \cdot \left\{ \sqrt{2} \cdot \sigma \cdot \left[ -\exp(-a_1^2) + (1 - T_p) \cdot \exp(-a_2^2) \right] + \sqrt{\pi} \cdot \mu \cdot \left[ -\text{erf}(a_1) + (1 - T_p) \cdot \text{erf}(a_2) \right] \right\}/\sqrt{\pi} \cdot \left[ \text{erf}(a_3) - \text{erf}(a_2) \right]
\]

\(f(T_o) = \frac{1}{k} \cdot \exp\left( \frac{-(T_o - \mu)^2}{2\sigma^2} \right), \quad k = \int_0^{T_p} \exp\left( \frac{(s - \mu)^2}{2\sigma^2} \right) \cdot ds\)

\(a_1 = \frac{\mu}{\sqrt{2} \cdot \sigma}, \quad a_2 = \frac{(\mu - 1)}{\sqrt{2} \cdot \sigma}, \quad a_3 = \frac{(\mu - T_p)}{\sqrt{2} \cdot \sigma}\)

and \(\exp()\) and \(\text{erf}()\) are the exponential and error functions, respectively.

Similarly,

\[
\text{Mean prob of opponent being hit } = \int_{T_o}^{T_p} f(T_o) \cdot (1 - T_o) \cdot T_p \cdot dT_o + \int_{T_o}^{T_p} T_p \cdot dT_o = T_p \cdot \left\{ \sqrt{2} \cdot \sigma \cdot \left[ -\exp(-a_1^2) + (1 - T_p) \cdot \exp(-a_2^2) \right] + \sqrt{\pi} \cdot \left[ (1 - \mu) \cdot \text{erf}(a_1) - \text{erf}(a_2) + \mu \cdot \text{erf}(a_3) \right] \right\}/\sqrt{\pi} \cdot \left[ \text{erf}(a_3) - \text{erf}(a_2) \right]
\]

Stochastic Determination of the Participant’s and Opponent’s Survival Outcomes for the Binary Outcome Feedback Mode

Table A1 summarizes the participant’s and opponent’s possible survival outcomes based on randomly generated numbers (RN) that determine whether a particular shot will hit its target if the opportunity to shoot is available. In essence, a shot will hit its target if RN (from 0 and 100 inclusive) is less than the shooting time of the shot being fired. For example, if the opponent’s shooting time is less than the participant’s shooting time (i.e., \(T_o < T_p\)), then the opponent has the first opportunity to shoot the participant, but a hit is realized only if \(RN_1 < T_o\). If not hit, the participant then has an opportunity to shoot the opponent, which in this case can occur only if \(RN_2 < T_p\). The remaining possibility is \(RN_1 \geq T_o\) and \(RN_2 \geq T_p\) in which case neither the participant nor opponent is hit. This time dependency of hit probabilities makes Table A1 more complicated than the usual form of outcome tables, which are confined to deterministic possibilities (i.e., consequences of actions without a stochastic dependency).

**TABLE A1: Summary of Possible Binary Outcomes of Surviving (√) and Being Hit (X)**

<table>
<thead>
<tr>
<th>Target</th>
<th>(T_o &lt; T_p)</th>
<th>(T_o \geq T_p)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(T_o &lt; T_p)</td>
<td>(T_o \geq T_p)</td>
</tr>
<tr>
<td></td>
<td>(RN_1 &lt; T_o)</td>
<td>(RN_2 &lt; T_p)</td>
</tr>
<tr>
<td>Participant</td>
<td>X</td>
<td>√</td>
</tr>
<tr>
<td>Opponent</td>
<td>√</td>
<td>X</td>
</tr>
</tbody>
</table>

Note. \(T_p\) and \(T_o\) are the shooting times of the participant and opponent, respectively, and \(RN_1\) and \(RN_2\) are randomly generated numbers. The possibility that both the participant and opponent are simultaneously hit is negligible and therefore ignored (see text).
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KEY POINTS

- For learnable tasks, the “outside view” of hit rate probability feedback facilitated learning better than the “inside view” of binary outcome feedback.
- For learned or almost learned tasks, hit rate feedback facilitated survival and target acquisition performance better than binary feedback.
- Although beneficial for learnable tasks, the “outside” versus “inside” performance feedback has an associated higher cost of cognitive processing manifested by higher decision response time.

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