

UC Merced

Proceedings of the Annual Meeting of the Cognitive Science Society

Title

Task Expectations Influence Learning from Feedback

Permalink

<https://escholarship.org/uc/item/2333q3pm>

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 40(0)

Authors

Fyfe, Emily R

Brown, Sarah A

Publication Date

2018

Task Expectations Influence Learning from Feedback

Emily R. Fyfe (efyfe@indiana.edu)

Department of Psychological and Brain Sciences, 1101 E. 10th Street
Bloomington, IN 47405 USA

Sarah A. Brown (sbrown23@wisc.edu)

Department of Psychology, 1202 W. Johnson Street
Madison, WI 53706 USA

Abstract

The effects of feedback often depend on individual learner characteristics. In the current study, we experimentally tested whether an individual's task expectations influence learning from feedback on mathematics problems. Specifically, we manipulated undergraduate students' beliefs about the difficulty of the task to influence their expectations for success. Students ($N = 160$) were randomly assigned to one of four learning conditions based on a crossing of two factors: task expectations (easy or hard) and feedback during problem solving (yes or no). On a final transfer test, feedback led to higher scores than no feedback for those who expected the task to be easy. But, feedback led to marginally lower scores for those who expected the task to be hard. Results suggest that expecting the task to be hard and to experience failure can lead to a self-fulfilling prophecy. When learning from feedback, students should set their expectations for success.

Keywords: feedback; problem solving; task expectations; individual differences; mathematics learning

Introduction

The role of feedback is central to many theories of learning. Even basic feedback can help reinforce accurate responses and correct inaccurate responses (see Mory, 2004). However, the effects of feedback are far from uniform. Based on a review of research, Hattie and Gan (2011) conclude that "feedback effects are among the most variable in their influence" (p. 249). Some of this variability is due to individual learner characteristics (e.g., Cianci, Schaubroeck, & McGill, 2010; Fyfe, Rittle-Johnson, & DeCaro, 2012). In the current study, we focused on individuals' task expectations and the efficacy of feedback during problem solving. Specifically, we manipulated students' expectations for success on the task to experimentally evaluate whether these expectations influence learning from feedback.

The Effects of Feedback

Feedback is a broad construct that can encompass many different types of information presented to a learner including grades, praise, and written or oral comments. In the current study, we focus on basic corrective feedback which provides targeted information about the accuracy of the learner's performance that can be used to confirm, reject, or modify prior knowledge of the target task (see Mory, 2004). Meta-analyses and reviews continue to show that this type of corrective feedback is often beneficial for

improving learning and performance (e.g., Bangert-Drowns, Kulik, Kulik, & Morgan, 1991; Hattie & Yates, 2014; Kluger & DeNisi, 1996; Shute, 2008). For example, one of the more comprehensive meta-analyses that incorporated 607 effect sizes and over 20,000 observations indicated that feedback had a significant positive effect ($d = .41$) relative to no feedback (Kluger & DeNisi, 1996). More recent research supports these conclusions as well. For example, in a series of experiments investigating the use of cognitive science principles in education, Kornell and Metcalfe (2014) found large benefits of corrective feedback for both adults and children learning target vocabulary words.

However, the benefits of feedback are not universal. Although feedback may have positive effects on average, there is large variability in these effects (e.g., Kluger & DeNisi, 1996). In fact, in a substantial minority of cases, feedback is not merely ineffective; rather, it hinders learning relative to a no-feedback control (e.g., Fyfe & Brown, 2017; Kluger & DeNisi, 1996; Pashler, Cepeda, Wixted, & Rohrer, 2005). Thus, research is needed to better understand what causes the effects of feedback to differ. This type of research will help inform theories of learning and also have practical implications for when to administer feedback.

Previous research has identified several factors related to the learning context that help explain some of these harmful effects (see Mory, 2004). For example, classic research in psychology suggests feedback can have hindering effects when it is available before or during the target response (e.g., correct answers in the back of the book) as it can lead to mindless processing of the material (Anderson, Kulhavy, & Andre, 1971). More recent research has focused more explicitly on factors related to the learner. For example, Cianci and colleagues (2010) found that negative feedback facilitated learning for individuals whose goal was to learn, but not for individuals whose goal was to demonstrate their abilities. Similarly, Fyfe and colleagues (2012) found that corrective feedback was beneficial for learners with low prior knowledge in the target domain, but detrimental for those with high prior knowledge. In addition to the learner's goals and prior knowledge, we speculate that the learner's *expectations* may influence learning from feedback.

Task Expectations

As with feedback, task expectations can take a variety of forms. In this study, we focus on expectations about success or failure on a target task. There are competing hypotheses

as to how these expectations may interact with the presence of feedback to influence learning. On the one hand, some lines of research suggest that expecting to fail may facilitate learning from feedback. Expecting to fail can be viewed as a self-preservation strategy called defensive pessimism (Norem & Cantor, 1986). The goal is to set one's expectations low to avoid any possible disappointment. In this case, the learner who expects to fail may not have an emotional response to negative feedback and therefore may have the cognitive resources to learn from it. Indeed, feedback intervention theory suggests that avoiding emotional, self-involved responses to feedback should increase the benefits of feedback (Kluger & DeNisi, 1996). Additionally, the learner who expects to fail but receives positive feedback may have heightened attention to the problems, an effect that has been shown in the memory literature (e.g., Fazio & Marsh, 2009).

Under this account, expecting to succeed carries the risk of disappointment. In this case, the negative feedback may be interpreted as a reflection of one's abilities that demotivates learning (e.g., Kluger & DeNisi, 1998).

On the other hand, different lines of research suggest that expecting to fail may hinder learning from feedback. Expecting to fail can be viewed as a type of threat situation that produces a self-fulfilling prophecy (e.g., Meron, 1948). Individuals who expect to do poorly may act in ways that confirm this expectation. For example, they may discount positive feedback and view negative feedback as a confirmation of their expectation. This is consistent with the behavior of individuals who expect to fail due to stereotype threat (e.g., Steele, 1997). Individuals in a threat condition often dismiss positive feedback and attend more to negative feedback (see Rydell & Boucher, 2017). Further, research suggests this attention to negative feedback is associated with poorer learning outcomes (Mangels et al., 2012).

Under this account, expecting to succeed may facilitate learning from feedback by empowering the learner. Rather than ruminating on the fact that the feedback was negative, individuals who expect success may try harder to learn from the available feedback, knowing they are capable. Indeed, in non-threat conditions, responses to negative feedback do not have the same hindering effects as they do in threat conditions when failure is expected (Mangels et al., 2012).

The Current Study

The goal of the present study was to evaluate these competing rationales by testing the effectiveness of feedback for individuals who expect to succeed versus individuals who expect to fail. We manipulated students' beliefs about the difficulty of a mathematics task to influence their expectations for success (see Swanson & Tricomi, 2014 for a similar technique). Then, we had them solve problems with or without corrective feedback on a trial-by-trial basis. Finally, students studied an instructional example and completed a posttest. Our primary goal was to assess whether students learned from the feedback differentially as a function of their expectations.

Method

Undergraduate students participated in a single one-on-one learning session in a laboratory setting. They completed a paper-and-pencil packet with target math problems. We manipulated their expectations before they solved the target problems and we manipulated the presence of feedback while they solved the target problems. The packet contained posterior probability problems, which can be used to calculate the prevalence of a condition (e.g., the likelihood that a person has this condition) and the predictive value of a test (e.g., the likelihood that a person who tested positive for this condition actually has this condition). See Figure 1.

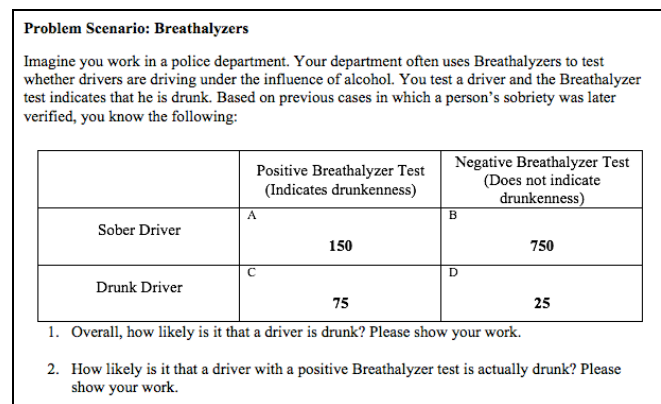


Figure 1: Example problems.

Participants

Participants were 160 undergraduate students from the University of Wisconsin-Madison. They received extra credit in their introductory psychology course in exchange for participation. Based on self-report, their average age was 19.3 years (SD = 1.5) and there were 107 females (67% of sample). Many students reported their ethnicity as White (67%) and the remaining students reported their ethnicity as Asian (19%), Hispanic or Latino (4%), Black or African American (2%), Native American (1%), or multiracial (7%).

Design and Procedure

Students were randomly assigned to one of four between-subjects conditions based on a crossing of two factors: (expectations: easy or hard) and (feedback: yes or no). During a one-on-one session, they completed a paper-and-pencil packet with four primary sections: (1) expectation manipulation and manipulation check problems, (2) target problems with or without feedback, (3) worked example lesson, and (4) posttest problems.

At the beginning of the one-on-one session, the experimenter explained that the researchers were interested in the strategies people use to solve math problems. Then, she manipulated task expectations. Students in the *expect-hard condition* were told the problems would be very difficult (e.g., "One of the reasons we are studying these problems is because they are extremely difficult. The vast

majority of people solve these problems incorrectly and we expect these problems to be difficult for you as well.”). Students in the *expect-easy condition* were told the problems would be very easy (e.g., “One of the reasons we are studying these problems is because they are extremely easy. The vast majority of people solve these problems correctly and we expect these problems will be easy for you as well.”). To check that the manipulation worked, students then solved two posterior probability problems and rated their confidence on each problem using a scale from 1 (*very unsure*) to 9 (*very sure*). If the manipulation worked, then students in the expect-hard condition should have lower confidence in their success than students in the expect-easy condition. However, their performance should be similar.

Students then proceeded to solve four target problems. Students in the *feedback condition* received verification feedback on their strategy and answer after each problem. If they solved it incorrectly, the experimenter said, “Actually, that is not a correct strategy to solve this problem.” If they solved it correctly, the experimenter said, “Great! You used a correct strategy to solve that problem and you got the correct answer.” After the feedback, students moved on to the next problem. Students in the *no feedback condition* received no input after each problem. Rather, the experimenter asked them to move on to the next problem.

After solving the target problems, students were instructed to study a worked example that provided a step-by-step solution for solving posterior probability problems. The example introduced students to a novel scenario and included a data table similar in structure to the data tables provided in previous problems. The example made explicit connections between the values in the written scenario and the values in the table, and demonstrated the solution.

The final section of the packet contained seven posttest problems to assess learning from the example lesson. The first two problems were isomorphic to the problems presented in the target feedback problems section and in the example lesson. We refer to these two problems as *learning problems*. The remaining five problems used different scenarios and table structures to assess transfer to novel problems. For example, several problems included data tables with four rows instead of two, which required students to generalize to a more complex set of numbers. We refer to these five problems as *transfer problems*.

At the end of the session, students completed an optional demographic survey and then they were debriefed. The experimenter explained the study, including the deception regarding the difficulty of the problems.

Scoring

We were primarily interested in participants’ strategy use, rather than their ability to perform the arithmetic steps; thus, we selected correct strategy use as our dependent measure. One researcher scored all participants’ written work for strategy correctness. A second researcher scored 25% of the items. The two coders agreed on strategy correctness for

99% of manipulation check problems, 98% of feedback problems, and 94% of posttest problems.

Results

First, we report on the initial manipulation check problems to ensure the expectation manipulation worked. Then, we report primary analyses on students’ performance on the posttest. We analyze learning problems and transfer problems as separate outcomes. For our primary analyses, we use analysis of variance (ANCOVA) to examine condition differences and we report partial eta squared values as a measure of effect size. According to Cohen (1988), values of .01, .06, and .14 can be interpreted respectively as small, medium, and large effects. We included two covariates: performance on the manipulation check items to control for baseline knowledge and total time on task given condition differences, $F(3, 155) = 3.63, p = .01, \eta_p^2 = .07$, with students in the expect-hard condition taking longer than students in the expect-easy condition.

Manipulation Check Problems

We predicted that the expectation manipulation would change students’ confidence in their baseline performance, but not their actual performance. That is what we found.

Performance on the two manipulation check items was low. The average score was 0.6 out of 2.0 ($SD = 0.8$). Conditions were well-matched in baseline performance. A 2 (feedback: yes or no) by 2 (expectations: easy or hard) ANOVA with number correct as the dependent variable revealed no significant effects, $p > .05$. See Table 1.

Table 1: Baseline performance and confidence ratings.

	Scores (out of 2)	Ratings (out of 9)
Expect Hard + No FB	0.8 (0.9)	4.3 (2.5)
Expect Hard + FB	0.5 (0.6)	4.3 (2.0)
Expect Easy + No FB	0.6 (0.7)	5.4 (2.6)
Expect Easy + FB	0.5 (0.8)	5.1 (2.7)

Average confidence ratings were in the middle of the scale ($M = 4.8, SD = 2.5, range = 1 - 9$). As expected, confidence ratings differed by condition. We ran a 2 (feedback: yes or no) by 2 (expectations: easy or hard) ANCOVA with average confidence ratings as the dependent variable and baseline performance as a covariate. There was a significant main effect of expectation condition, $F(1, 155) = 12.46, p = .001, \eta_p^2 = .07$. Students who expected the task to be hard had lower confidence ratings ($M = 4.2, SD = 2.3$) than students who expected the task to be easy ($M = 5.2, SD = 2.6$). There was not a significant main effect of feedback or a feedback by expectation interaction, $F_s < 1.0, p_s > .05$.

Overall, students were fairly good at monitoring their performance. Students who answered the items correctly tended to be more confident in their answers. For example, students who solved both baseline problems correctly had significantly higher confidence ratings ($M = 6.3, SD = 2.2$)

than students who solved zero or one problems correctly ($M = 3.6, SD = 2.1$), $F(1, 158) = 59.16, p < .001, \eta_p^2 = .27$. Similarly, among the 41 students who answered one item correctly and one item incorrectly, their confidence ratings were higher on the correct item ($M = 6.3, SD = 2.4$) than on the incorrect item ($M = 5.6, SD = 2.3$), $t(40) = 2.70, p = .01$. The accuracy of monitoring performance did not appear to differ by condition. For example, within all four conditions, students who solved both baseline problems correctly had significantly higher confidence ratings than students who solved zero or one problems correctly, $ps < .05$.

Thus, students had somewhat low performance on the baseline problems and their confidence in that performance varied. Importantly, the expectation manipulation was successful; students who expected the task to be hard had lower confidence than students who expected the task to be easy. Otherwise, conditions were well-matched.

Posttest Learning Problems

Performance on the two learning problems at posttest was high ($M = 1.4, SD = 0.7$), and was significantly better than performance on the two baseline manipulation check problems, paired samples $t(159) = 13.05, p < .001$. Thus, in general, the problem solving and example lesson promoted learning of the target material within the sample as a whole.

To examine condition differences, we conducted a 2 (expectations: easy or hard) by 2 (feedback: yes or no) ANCOVA with learning scores (out of 2) as the dependent variable. We included baseline performance and total time on task as covariates. There was not a main effect of expectation condition or an expectation-by-feedback interaction, $F_s < 2, ps > .05$. Rather, there was a significant main effect of feedback, $F(1, 153) = 4.33, p = .04, \eta_p^2 = .03$. As shown in Figure 2, students who received feedback had higher learning scores ($M = 1.5, SE = 0.1$) than students who did not ($M = 1.2, SE = 0.1$), regardless of task expectations.

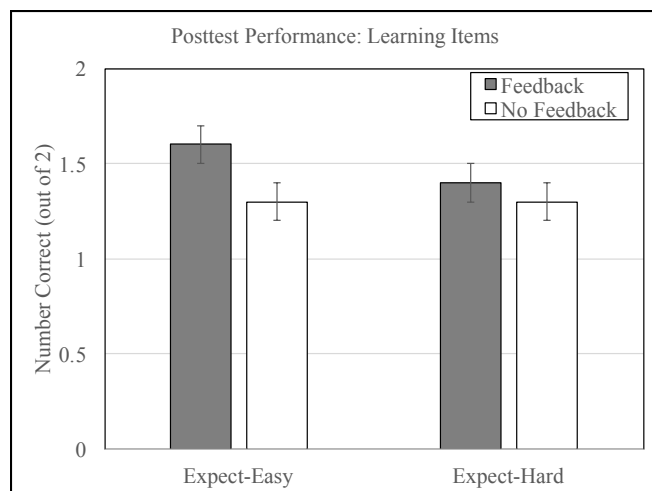


Figure 2: Posttest learning scores by condition.

Posttest Transfer Problems

Performance on the five transfer problems at posttest was low to moderate ($M = 2.1, SD = 1.1$), which was expected given the novelty of the problems.

To examine condition differences, we conducted a 2 (expectations: easy or hard) by 2 (feedback: yes or no) ANCOVA with transfer scores (out of 5) as the dependent variable. We included baseline performance and total time on task as covariates. There were not main effects of expectation condition or feedback condition, $F_s < 1, ps > .05$. Rather, there was a significant expectation-by-feedback interaction, $F(1, 153) = 6.10, p = .015, \eta_p^2 = .04$. To follow up the interaction, we examined the main effect of feedback within each expectation group. For students in the expect-easy condition, there was a significant positive effect of feedback, $F(1, 153) = 4.20, p = .04, \eta_p^2 = .03$. As shown in Figure 3, students who received feedback had higher transfer scores ($M = 2.4, SE = 0.2$) than students who did not ($M = 1.9, SE = 0.2$). However, for students in the expect-hard condition, there was a marginal negative effect of feedback, $F(1, 153) = 3.55, p = .06, \eta_p^2 = .02$. As shown in Figure 3, students who received feedback had lower transfer scores ($M = 1.8, SE = 0.2$) than students who did not ($M = 2.3, SE = 0.2$).

Thus, feedback influenced students' posttest performance, but the effect depended on students' expectations.

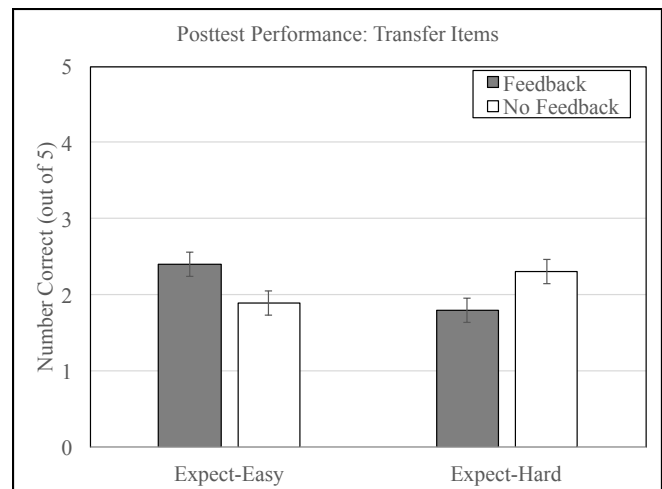


Figure 3: Posttest transfer scores by condition.

Discussion

In the current study, we experimentally tested whether one's task expectations influence learning from feedback on target math problems. We manipulated undergraduate students' beliefs about the difficulty of the task and their expectations for success. Then, we had them solve target problems with or without corrective feedback. Students across conditions exhibited some learning from feedback and the instructional example. On the posttest learning items, there was a significant positive effect of feedback relative to no feedback. But, task expectations influenced students' ability

to learn from feedback in a deep way that resulted in transfer. For students who expected to succeed, feedback had a positive effect on their posttest transfer scores relative to no feedback. In contrast, for students who expected to fail, feedback had a marginally negative effect on their transfer scores relative to no feedback. The current study provides causal evidence that feedback can have different, though small effects depending on one's expectations.

The present findings contribute to the literature on feedback in several key ways. First, they are consistent with the conclusion that feedback has highly variable effects (e.g., Hattie & Gan, 2011; Kluger & DeNisi, 1996). That is, sometimes providing feedback promotes learning and performance, but sometimes providing feedback reduces learning relative to a no-feedback control. Importantly, the pattern of mixed effects in the current study suggest that even when feedback provides useful information, it can have mixed consequences. That is, the current results suggest there was not a deficiency in the type of feedback provided per se (e.g., the feedback was effective for some outcomes and some learners); rather, what mattered was the learners' *interpretations* of the feedback message in light of their expectations.

Thus, a second contribution to the feedback literature is to support the notion that learner characteristics are at least as important as characteristics of the feedback itself. Indeed, a growing number of studies have demonstrated that the influence of feedback depends on a variety of learner characteristics including prior knowledge (e.g., Nihalani Mayrath, & Robinson, 2011), learning goals (e.g., Cianci et al., 2010), and working memory (e.g., Fyfe, DeCaro, & Rittle-Johnson, 2015). The present findings suggest that differences in task expectations may also play a key role. Students in the expect-easy condition who expected to succeed benefitted from feedback on the transfer posttest. However, students in the expect-hard condition who expected to fail were somewhat hindered by feedback on the transfer posttest. One key question for consideration concerns the mechanisms behind these differential effects.

One possibility is that expecting to fail produces a self-fulfilling prophecy (Merton, 1948) that inhibits learning from feedback. Expecting to fail can lead one to dismiss positive feedback and to view negative feedback as a confirmation that the task is unachievable (e.g., Rydell & Boucher, 2017). This, in turn, may demoralize students and lead them to abandon subsequent attempts at learning. In this case, problem solving without feedback may produce more desirable learning outcomes.

A second possibility is that students in the current study benefitted more from surprising feedback (see Fazio & Marsh, 2009). In this study, students in the expect-easy condition may have been more surprised when they received negative feedback relative to students in the expect-hard condition. This element of surprise may have spurred heightened task-relevant attention to the feedback in a way that promoted subsequent learning and transfer. Future research is needed to tease apart these various explanations.

Several limitations of this study suggest additional directions for future research. For example, future research should assess students' existing, authentic task expectations and how they influence learning from feedback. In the current study, we used a paradigm from prior research (e.g., Cianci et al., 2010; Swanson & Tricomi, 2014) in which we manipulated students' beliefs about task difficulty to influence their expectations for success. Although evidence suggests our manipulation worked (e.g., students who were told that the task would be easy had higher confidence ratings relative to students who were told that the task would be hard), assessing the effects of feedback in relation to students' deep-seated or longstanding expectations about a meaningful task would increase the validity of the results.

Additional studies should also consider using different types of feedback. In the current study, we employed verification feedback. Prior research suggests that very basic verification feedback can be effective, but not as effective as other types (e.g., Fazio, Huelser, Johnson, & Marsh, 2010). We did use feedback that focused both on students' solution strategies and their answers. Further, we included an instructional worked example as well as to assess how feedback prepares students to learn from additional material. However, future research should include variations in the type and timing of feedback in relation to task expectations. It may be that task expectations influence students' interpretations of verification feedback differently than other forms of feedback.

Finally, future research should replicate the current study using different tasks and topics, particularly given the fact that the effect sizes were small. We selected base rate probability problems because they rely on mathematics reasoning and are critical for interpreting information in real-world scenarios (e.g., Hoffrage et al., 2005), yet people often struggle to solve them correctly. Further, we wanted to assess the effects of feedback on a problem-solving task in which generating and executing strategies is critical for success. However, to better understand the interactions between task expectations and the efficacy of feedback, it will be necessary to assess their effects on different types of knowledge using a variety of different outcomes.

Despite these limitations, the current study has important implications for the role of feedback in formal and informal learning settings. For example, the present evidence suggests that there are situations in which basic verification feedback can benefit learning. Thus, it is not the case that expansive feedback is always necessary to promote positive outcomes. The present evidence also suggests that when learning from feedback, students should set their expectations for success. Intuitively, there may be some concern that setting students' expectations too high may result in disappointment and demotivation when those expectations are not met. That was not the case here. In fact, it was the students who expected to fail who did not benefit from the feedback. Telling students that the problems were easy and that they should succeed may have shielded them from the disappointment that arises from receiving feedback

on one's errors, thereby making them more resilient. In general, learning from feedback during problem solving is effective when students set their expectations for success.

Acknowledgments

Support for this research was provided in part by Institute of Education Sciences, U.S. Department of Education, training grant R305B130007 as part of the Wisconsin Center for Education Research Postdoctoral Training Program. The authors would like to thank Haley Beers and Alexis Hosch for help with data collection and coding.

References

- Anderson, R. C., Kulhavy, R. W., & Andre, T. (1971). Feedback procedures in programmed instruction. *Journal of Educational Psychology, 62*, 148-156.
- Bangert-Drowns, R. L., Kulik, C., Kulik, J. A., & Morgan, M. (1991). The instructional effects of feedback in testlike events. *Review of Educational Research, 61*, 213-238.
- Cianci, A. M., Schaubroeck, J. M., & McGill, G. A. (2010). Achievement goals, feedback, and task performance. *Human Performance, 23*, 131-154.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: Erlbaum.
- Fazio, L. K., & Marsh, E. J. (2009). Surprising feedback improves later memory. *Psychonomic Bulletin Review, 16*, 88-92.
- Fazio, L. K., Huelser, B. J., Johnson, A., & Marsh, E. J. (2010). Receiving right/wrong feedback: Consequences for learning. *Memory, 18*, 335-350.
- Fyfe, E. R., & Brown, S. A. (2017). Feedback influences children's reasoning about math equivalence: A meta-analytic review. *Thinking and Reasoning*.
- Fyfe, E. R., DeCaro, M. S., & Rittle-Johnson, B. (2015). When feedback is cognitively-demanding: The importance of working memory capacity. *Instructional Science, 43*, 73-91.
- Fyfe, E. R., Rittle-Johnson, B., & DeCaro, M. S. (2012). The effects of feedback during exploratory mathematics problem solving: Prior knowledge matters. *Journal of Educational Psychology, 104*, 1094-1108.
- Hattie, J., & Gan, M. (2011). Instruction based on feedback. In R. Mayer & P. Alexander (Eds.), *Handbook of research on learning and instruction*. NY: Routledge.
- Hattie, J., & Yates, G. (2014). Using feedback to promote learning. In V. A. Benassi, C. E. Overson, & C. M. Hakala (Eds.), *Applying science of learning in education: Infusing psychological science into the curriculum*. Retrieved from the Society for the Teaching of Psychology website: <http://teachpsych.org/ebooks>
- Hoffrage, U., Kurzenhauser, S., & Gigerenzer, G. (2005). Understanding the results of medical tests: Why the representation of statistical information matters. In R. Bibace, J. D. Laird, K. L. Noller, & J. Valsiner (Eds.), *Science and medicine in dialogue*. Westport: Praeger Publishers.
- Kluger, A. N., & DeNisi, A. (1996). Effects of feedback intervention on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. *Psychological Bulletin, 119*, 254-284.
- Kluger, A. N., & DeNisi, A. (1998). Feedback interventions: Toward the understanding of a double-edged sword. *Current Directions in Psychological Science, 7*, 67-72.
- Kornell, N., & Metcalfe, J. (2014). The effects of memory retrieval, errors, and feedback on learning. In V. A. Benassi, C. E. Overson, & C. M. Hakala (Eds.), *Applying science of learning in education: Infusing psychological science into the curriculum*. Retrieved from the Society for the Teaching of Psychology website: <http://teachpsych.org/ebooks>
- Mangels, J. A., Good, C., Whiteman, R. C., Maniscalco, B., & Dweck, C. S. (2012). Emotion blocks the path to learning under stereotype threat. *Social Cognitive and Affective Neuroscience, 7*, 230-241.
- Merton, R. K. (1948). The self-fulfilling prophecy. *The Antioch Review, 8*, 193-210.
- Mory, E. H. (2004). Feedback research revisited. In D. Jonassen (Ed.), *Handbook of research on educational communications and technology*. Mahwah, NJ: Erlbaum.
- Nihalani, P. K., Mayrath, M., & Robinson, D. H. (2011). When feedback harms and collaboration helps in computer simulation environments: An expertise reversal effect. *Journal of Educational Psychology, 103*, 776-785.
- Norem, J. K., & Cantor, N. (1986). Anticipatory and post hoc cushioning strategies: Optimism and defensive pessimism in "risky" situations. *Cognitive Therapy and Research, 3*, 347-362.
- Pashler, H., Cepeda, N. J., Wixted, J. T., & Rohrer, D. (2005). When does feedback facilitate learning of words? *Journal of experimental psychology. Learning, Memory, and Cognition, 31*, 3-8.
- Rydell, R. J., & Boucher, K. L. (2017). Chapter two: Stereotype threat and learning. *Advances in Experimental Social Psychology, 56*, 81-129.
- Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*, 153-189.
- Steele, C. M. (1997). A threat in the air: How stereotypes shape intellectual identity and performance. *American Psychologist, 52*, 613-629.
- Swanson, S. D., & Tricomi, E. (2014). Goals and task difficulty expectations modulate striatal responses to feedback. *Cognitive, Affective, and Behavioral Neuroscience, 14*, 610-620.