Effect of Feedback with Video-based Peer Modeling on Learning and Self-efficacy

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Abstract
In this study, we examined the effect of video-based feedback designed to highlight a peer engaging in effective thinking processes on self-efficacy beliefs and learning outcomes (performance on a delayed quiz). Students in an introductory statistics course participated in an online learning activity where they received feedback in one of three randomly assigned conditions: a video of a peer demonstrating the process of arriving at a correct answer (mastery condition), a peer making mistakes then self-correcting those errors before arriving at a correct answer (coping condition), or a screenshot of a peer's correct worked example (as a control). Results indicated that students who watched the mastery videos, but not the coping videos, rated their self-efficacy higher and scored higher on a class quiz taken more than a day after the feedback intervention than students who viewed a worked example. However, students in the two video conditions did not significantly differ in terms of either self-efficacy and quiz performance. The results of this study, although modest in scope, illustrate how the design of feedback could lead to noticeable differences in student learning.

Keywords: video-feedback, peer-learning, self-efficacy

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Feedback is critical to learning, but some feedback is more effective than others (Hattie & Timperley, 2007). In online environments, feedback is typically outcome feedback—feedback that shows whether an answer is correct or the proportion of correct responses. Outcome feedback is usually shown after a student provides their responses (Geister et al., 2006), and offers some advantages; for instance, it can be delivered immediately to students during learning and can be implemented in several ways (e.g., text, color-coded responses, sound effects). However, the quickness and ease of showing students such outcome feedback often obscures the process by which students can achieve some desired outcome. In other words, outcome feedback shows the *ends* but what we want students to learn is the *means*. Synchronous, in-person, or more personalized instruction more often focuses on these processes (Korsgaard & Diddams, 1996).

The purpose of this study is to examine ways to emulate this richer, process feedback in asynchronous, online instruction. Such instruction is increasingly common as the use of interactive online textbooks and learning materials require students to engage in independent technology-mediated learning. An advantage of doing research that can be implemented in online textbooks is that insights gained can immediately be integrated into the product, thus impacting many users and teachers (e.g., Stigler et al., 2020). The results of the study reported here, a tightly controlled experiment to find out how to give more effective feedback, are not restricted to an academic journal article—they can be directly integrated in a free interactive online textbook called *Statistics and Data Science: A Modeling Approach* (see Son & Stigler, 2017–21) currently used by thousands of students. The "better book" approach to education research and development has the potential to close longstanding gaps between research and practice (Stigler et al., 2020). The experimental takeaways about feedback can also be implemented in other kinds of online learning experiences (e.g., MOOCs) and technologies.

We tested the effect of three different types of feedback on students' learning and transfer of programming and data analysis concepts. Inspired by how effective feedback is given in synchronous learning contexts, we investigated whether process feedback delivered through social modeling might benefit learning and transfer more than process feedback delivered through text. Extensive research has shown that people learn from observing and imitating others. People often change their expectations and strategies after watching others. Watching others can also affect social-cognitive and motivational processes such as self-efficacy (Schunk & Zimmerman, 1997, 2007). Given these findings, asynchronous, online feedback carefully designed to maximize the effects of social modeling has the potential to confer cognitive and noncognitive benefits during learning.

Literature Review

Benefits of process feedback

Students often need feedback that contains information beyond whether an answer is correct. For example, when a student is stuck on a wrong answer and does not know what to do when they are stuck, it may help to have feedback that provides insights on *how* to improve (Geister et al., 2006). Insightful teachers and coaches may implement this naturally in synchronous, face-to-face settings. For example, in a study investigating the verbal feedback of a highly successful basketball coach, John Wooden, over 65% of the comments given during practice focused on what the players needed to do to improve, not just that they were wrong or what they did wrong (Tharp & Gallimore, 1976). Much research shows that such process feedback—feedback that includes information about actions or strategies to improve—benefits learning over and above feedback that solely provides performance information. In a meta-analysis of studies investigating the effects of different forms of feedback on learning in face-to-face classrooms, the largest effect sizes were reported in studies in which students received such process feedback (Hattie & Timperley, 2007).

Although process feedback has been far less studied compared to outcome feedback, its effects have been explored in a variety of contexts and have been shown to affect learning in many ways (Geister et al., 2006; McLeod et al., 1992; Rust et al., 2003; van Gog, Paas, van Merriënboer, 2006; Ketchum et al., 2020). One way to provide process feedback is through examples (see van Gog & Rummel, 2010 for a comprehensive review of the research on example-based learning).

Worked examples—examples that provide the problem-solving steps that lead to the eventual solution—have been shown to facilitate performance in domains like math, physics, and computer science (Renkl, 2005); such worked examples also seem to be especially helpful for skill acquisition in the early stages of learning (Atkinson et al., 2000; Huang et al., 2015; Renkl, 2005; Sweller et al., 1998).

One potential mechanism to explain the effect of worked examples is cognitive load. Showing the students a worked-out solution reduces the strain on their working memory, which allows them to focus more holistically on the problem-solving process rather than the details associated with each step of the problem solution (Sweller, 1988; Sweller et al., 1998). In addition, worked examples may also help students by providing information about problem-solving strategies, modeling multiple solutions, and stimulating metacognitive strategies such as reflection and self-monitoring (Hawe et al., 2019).

Traditionally, research on worked examples has focused on *static* examples. However, process feedback can also be delivered *dynamically,* such as when people work through examples together or students watch a model work through examples. In computer science education, for example, live coding—the process of writing code in front of students during lecture—has been shown to support strategy development and engagement more than viewing a static worked example (Brown & Wilson, 2018; Robbins, Rountree, & Rountree, 2003; Rubin, 2013). Beyond providing information about problem-solving strategies, working through examples dynamically can also help to direct students' attention and engage students in active learning processes, such as questioning and elaboration. For example, the process of coding "live" slows instructors down, allowing more time for students to process the material and ask questions (Paxton, 2002). Instructors can also solicit and correct students' misconceptions in the moment (Vihavainen et al., 2011).

As more learning occurs online, both synchronously and asynchronously, researchers have begun to explore a variety of ways to implement process feedback in these novel environments. Prior studies have largely implemented text-based feedback, such as static worked examples (Gee, 2009; Zhi et al., 2019) and "just-in-time" prompts (Graesser et al., 1999). However, little has been done to explore the effect of different implementations of process feedback (e.g., dynamic versus static) in asynchronous online learning contexts. Although some work has explored possible non-cognitive benefits of dynamic feedback (e.g., in Rubin [2013] students report enjoying live coding as feedback), there is little research on how to effectively increase the non-cognitive benefits of dynamic feedback.

To address these gaps in the literature, our present study focuses on these research questions: How should we implement process feedback in an asynchronous learning context? Can well-designed process feedback impact both students' learning as well as attitudes around their own learning? We propose that dynamic feedback implemented as video-based peer models can result in both cognitive and non-cognitive benefits. For this study, we define *video-based peer modeling* as videos in which a peer model is shown performing a task or activity similar to one that the learner has just attempted.

Our hypothesis draws upon a rich literature in psychology regarding the role of social models and implements these ideas in an online, asynchronous learning environment with brief videos of a peer model. In the following section, we will draw the links between prior work on peer modeling and the possible mechanisms that would lead to cognitive and non-cognitive benefits.

Implementing process feedback with video-based peer models

There have been many demonstrations of the positive impact of peer models in face-to-face settings (Schunk et al., 1987; Ledford & Wolery, 2015), but a growing body of research suggests that video-based models may similarly promote learning in online settings. Video-based models have been used to promote motor skill development (i.e., Obrusnikova & Rattigan, 2016), problem-solving (Hoogerheide et al., 2014), and have been shown to support learning in unstructured, creative domains (Groenendijk et al., 2011). Most of these studies have used video-based examples as a way to introduce new skills and knowledge; few studies have investigated the use of video-based modeling as feedback *after* students have completed a task.

Unlike other forms of process feedback, which focus on cognitive and metacognitive strategies, video-based peer modeling may play an outsized role in the non-cognitive aspects of learning. Social Learning Theory (Bandura, & McClelland, 1977; Maisto et al., 1999) proposes that new skills and behaviors are acquired by observing and imitating others. Observing a peer attempt the same problem that the learner just attempted may offer the potential to provide key social and attitudinal information. For example, video-based models have also been shown to increase self-efficacy (Raedts et al., 2007), helping learners feel as though they too have the capacity to perform and learn to excel in difficult tasks. Such social information can buffer against negative experiences (e.g., failures, barriers) and promote self-regulation during learning (i.e., Delen et al., 2014). Adding even a small amount of social information to feedback has been shown to affect students positively. For example, personifying feedback by adding a friendly face made novice programmers more likely to persist during a computer programming activity (Lee & Ko, 2011).

Much of the research on peer modeling has assumed that similarity and connectedness to the peer drive much of the positive effects on learning and self-efficacy (i.e., Braaksma et al., 2002). Although there has been active research interest in different types of peer models, less is known about the behavior of peer models in the videos, that is, what the model should be doing and saying as they provide feedback to the learner. For example, should the model exemplify the errors that learners are likely to make as well as the solutions to remedy those errors? Or should the model give guidance on the correct path to take? The former is called a coping model while the latter is called a mastery model.

The few studies that have attempted to contrast the coping and mastery models have found that both lead to better performance compared to no model (Schunk & Hanson, 1989; Klorman et al., 1980; Selzler et al., 2020) but there is some hint that the coping model might have some slight advantage in particularly difficult situations (Selzler et al., 2020), possibly by demonstrating how to respond to difficulties, failure, and barriers during learning. In health contexts, for example, coping models have been shown to help people cope with stressful medical procedures, possibly because they increase self-efficacy for coping and reduce anxiety and avoidance-related behaviors (i.e., Selzler et al., 2020). Coping models have also been used to facilitate athletic skill acquisition. For example, Kitsantas et al. (2000) showed that girls who watched a peer struggle and then eventually master a difficult dart-throwing technique showed increased self-efficacy, interest, and dart skills than girls who watched a peer master the technique right away.

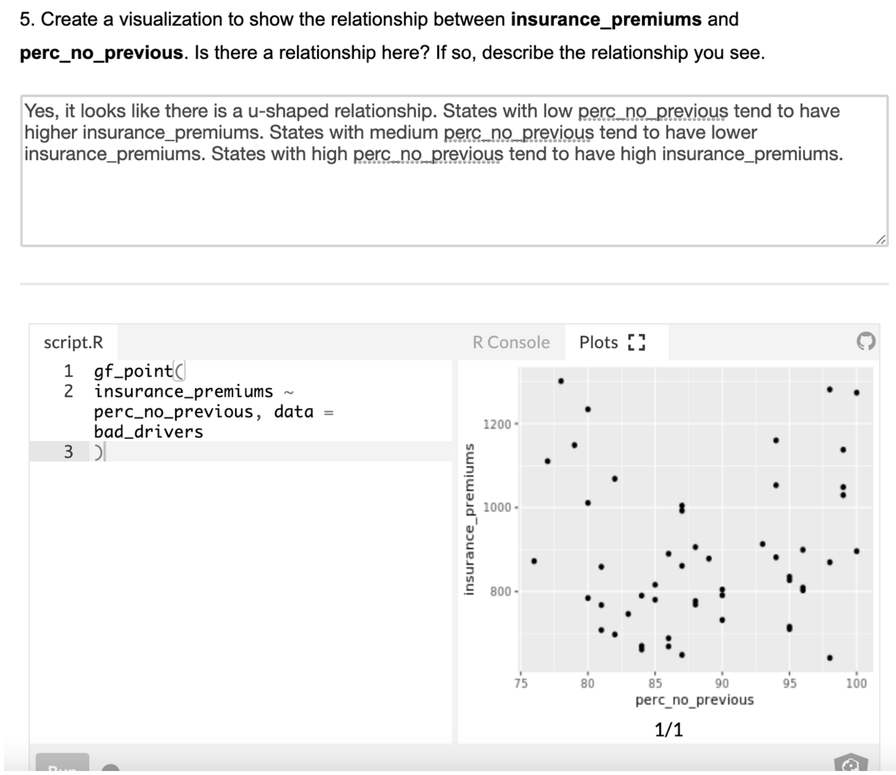
Given these findings, it is possible that coping models may benefit learning and self-regulation in academic contexts. However, few studies have investigated the potential benefits of coping in higher education settings. In addition, previous studies comparing the effects of coping and mastery models have focused on coping and mastery models as a form of initial instruction delivered *before* students have attempted a problem on their own. Whether coping and mastery models are effective forms of *feedback* is not yet known.

Present Study

To address these apparent gaps in the literature, we investigated the potential benefits of a video-based peer modeling intervention in which students received different forms of process feedback during an interactive problem-solving activity. The activity was similar in format to pages of the free interactive textbook our university student participants were using in their statistics course (Son & Stigler, 2017–21): text and figures interleaved with brief coding exercises. After the coding exercises, students received different types of feedback.

Students were randomly assigned to receive one of two peer-modeling videos: (1) a coping model where the peer modeled first making mistakes then remedying those mistakes and (2) a mastery model in which the peer modeled the correct answer. There were also students randomly assigned to a worked example condition serving as a comparison group. In this condition, students saw a static screenshot of another students' correct solution and the code they used to produce it. It is worth noting that in all three conditions (mastery, coping, and worked example), the feedback provided is process feedback. The difference is that the worked example is a type of *static* feedback (a still picture of the components of the solution) whereas the two types of peer-modeling feedback, coping and mastery, are *dynamic* feedback implemented as videos. After engaging students in the feedback activity, we then measured the effect of the intervention on students' beliefs about their ability to succeed on a delayed quiz and on their actual quiz performance.

Figure 1
Screenshot of a worked example



The video feedback conditions in our study implemented dynamic feedback with a special focus on capitalizing on the benefits of peer modeling by making the model's implicit thinking and decision-making process more explicit. The goal was to show students the intermediary steps necessary in approaching more complex problems, the timing of the outcome (e.g., that the solution isn't an instantaneous "Eureka!" moment), and the strategies that can be effective (e.g., some parts of the solution are easier to start with first). In the coping condition, the goal was to model the process of mistake-making and struggle, demonstrating how to react when a solution does not work as expected and strategies that can be implemented when faced with a setback. We hypothesized that both the coping and mastery feedback will lead to enhanced self-efficacy and cognitive performance than the worked example feedback.

To summarize, this study adds to the existing literature on feedback and learning in three important ways. First, this study combines the use of video-based feedback and peer models to mimic process feedback in an asynchronous, online learning environment. Second, unlike past studies of online feedback that have mainly focused on cognitive outcomes such as enhancing students' learning of concepts and strategies (i.e., Pratiwi et al., 2018) this study also includes socio-emotional outcomes. Thus, we examine both measures of self-efficacy and cognitive performance. Finally, to date, most studies examining video-based peer modeling have focused on the type of person who is the peer model. Little is known about the content of the model—what the model should *do*. We compared two different types of video-based models hypothesized to support learning: a mastery model in which a peer demonstrates an effective problem-solving process without making any mistakes and a coping model in which a student model makes and corrects mistakes.

Method

Participants

Participants were 208 undergraduate students enrolled in a 10-week introductory statistics course offered through the psychology department at the University of California, Los Angeles during the winter 2020 quarter. Because this class was a prerequisite class for students to major in psychology, students in this class were mostly pre-psychology majors. Due to the impact of COVID-19, the class was taught in person for the most part but switched to an online format at the end. All data collection for this study concluded before COVID-19 lockdowns and the switch to remote schooling began. The class had weekly homework from the online textbook and five quizzes throughout the 10-week period.

For their participation, students were offered extra credit. We excluded participants who did not consent to share their course data (n = 12) and students who did not complete the experiment (n = 46), creating an analytic sample of 162 students. Students were determined to have completed the experiment if they answered the questions on both the pre- and post-surveys and if they spent at least 30 seconds on pages that included videos (video conditions). The final sample included 57 students in the worked example condition, 54 in the mastery condition, and 51 in the coping condition. They were traditional college-aged students, with the majority of ages ranging between 18 and 24. The sample was mostly female (77.78%) and the majority of students were in their second or third year (80.50%) at the university.

Procedure & Materials

Participants were randomly assigned to one of three feedback conditions (worked example, mastery, or coping). Students were told that this online activity would help them prepare for an upcoming quiz. In the activity, students were presented with a dataset about insurance prices in the United States. They were asked eight questions and used R, a statistical programming language, to analyze the provided data set (coding windows were embedded in the online activity). After each question, students were provided with feedback based on their randomly assigned condition.

Feedback. In the worked example condition, the feedback was a screenshot of a peer's correct response after completing an exercise. In the other two modeling conditions, the feedback was an embedded video of a student thinking aloud while solving the same problem. In the coping condition, the model made an error common to that type of problem, realized their mistake, then self-corrected. In the mastery condition, the model's strategy and answer were correct. For example, one of the questions in the activity asked students to find the highest value in an array or list of numerical values. The student model in the mastery video sorted the list variable from highest to lowest values and then printed out the first five entries of the new array to the console. In contrast, the student model in the coping video first made the mistake of simply printing out the unorganized list of numerical values and then realized he needed to order the list. From there, the video matched the mastery condition, and the student correctly ordered and printed out the list.

Both mastery and coping videos included both the screen recording of the R programming activity and a smaller window featuring a talking-head-style shot of the student model (see Figure 2). The duration of the videos ranged from 47 to 299 seconds. Each feedback video was presented after students submitted their answers to a question. The total duration of videos in the coping condition was 907 seconds and the total duration of videos in the mastery condition was 1094 seconds. Two of the videos (1 and 6) were the same for students in both conditions (these videos did not feature a common error because the questions were relatively simple). Table 1 shows the duration of the videos for each condition.

Figure 2

Screenshot from one of the videos shown to students after each practice activity

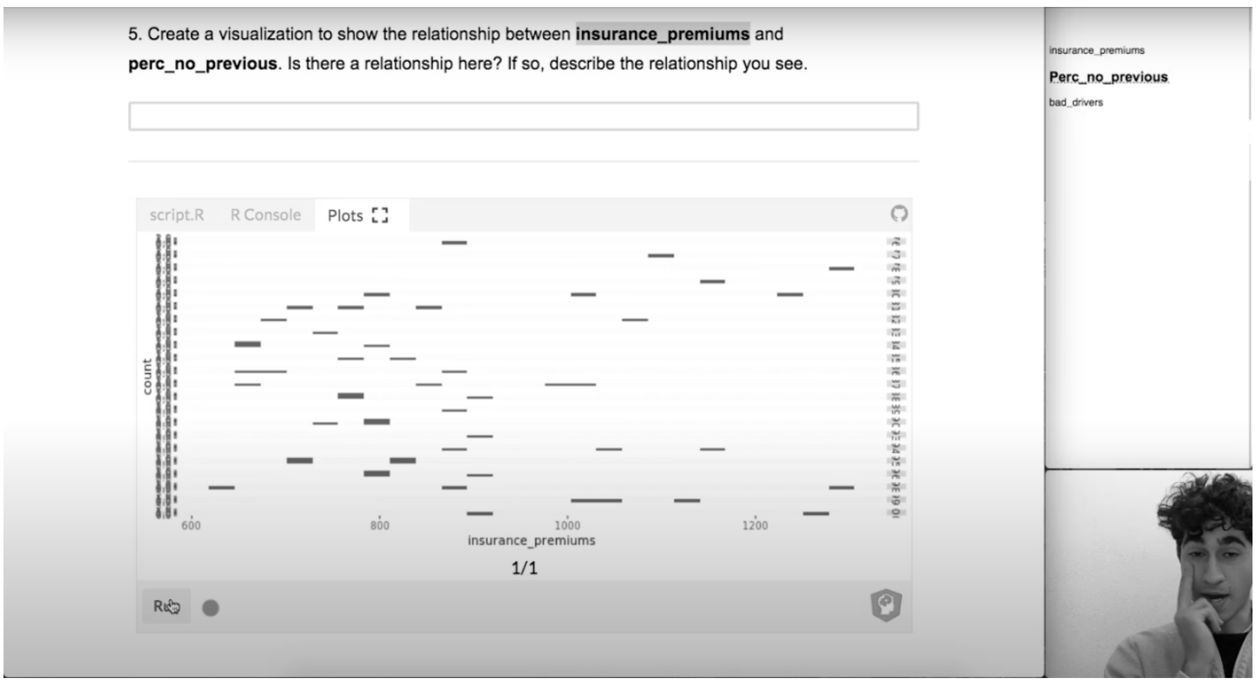


Table 1

Duration of the Peer Modeling Videos

Condition	Video								Total *Mins.* (s)
	1 Length *Mins.* (s)	2 Length *Mins.* (s)	3 Length *Mins.* (s)	4 Length *Mins.* (s)	5 Length *Mins.* (s)	6 Length *Mins.* (s)	7 Length *Mins.* (s)	8 Length *Mins.* (s)	
Mastery	2:04	1:46 (106)	1:39 (99)	1:01 (61)	2:05 (125)	2:36	0:47 (47)	3:09 (189)	(1094)

Coping	(124)	2:53 (173)	2:08 (128)	1:31 (91)	2:22 (142)	(156)	0:51 (51)	3:49 (229)	(907)

Note. Videos 1 and 6 (shaded in gray) were the same length for both conditions.

Measures

Performance. As a delayed, authentic measure of learning from this asynchronous activity, we collected students' scores on a weekly quiz that took place approximately two to three days after the intervention. The quiz included 17 questions that covered basic data analysis concepts (e.g., inspecting a dataset, creating graphs to visualize relationships, fitting simple linear regression models, creating ANOVA tables) and were aligned with the tasks students completed during the intervention. As in the intervention, students were given an unfamiliar dataset and asked to write and interpret R code to answer questions about those data. Of the 17 questions, four were open-ended responses, eight required students to generate R code, and five were multiple choice questions that required students to interpret R code or output. The open-ended response and coding questions were graded by the instructional team. Quiz scores were calculated as the number of questions answered correctly out of 17, with higher scores representing higher quiz performance.

Self-efficacy. Students rated self-efficacy by indicating confidence in five scenarios (i.e., *Earn an A on the next quiz; using R to analyze a new data set; achieving the goals you set for yourselves in this course; overcoming challenges in this course; and performing effectively on many different tasks in this course*). All five scenarios were also rated on a 5-point rating scale from “not at all confident” to “extremely confident.” These ratings were averaged together for one composite self-efficacy score. The Cronbach’s Alpha for the self-efficacy items was α = .933, 95% CI[.913, .947].

Perceived similarity to the peer model. Immediately after the online activity, students reported their perceived similarity to the peer model, self-efficacy, and evaluated the activity. Students judged their similarity to the model (*Think about the student whose responses you saw after each question. How similar is that student to you when it comes to this course?*) using a single item with a 5-point rating from “not at all like me” to “extremely like me.”

Perceptions of the activity. Students rated the activity by indicating agreement with three statements (i.e., *I think the instructor should use more activities like this throughout the course. I learned a lot from this activity. I would be interested in doing another activity like this to prepare for the final exam.*) using a 7-point rating scale from “strongly disagree” to “strongly agree.” All three ratings were averaged together to create a composite activity evaluation score. Higher scores indicate more positive perceptions of the learning activity. The Cronbach’s Alpha for the activity rating items was α = .885, 95% CI[.834, .923].

Analysis

The data were analyzed using multiple regression and ANOVAs in R version 3.6.2 (R Core Team, 2019). The focal predictor was the experimental condition. The outcomes of interest were self-efficacy and quiz performance. We predicted that students in the two *video-based peer modeling (dynamic feedback)* conditions would rate their self-efficacy higher and perform better on the quiz than students in the worked example condition.

Additionally, we predicted that perceived similarity—how similar the students rated the model to be to themselves—would be positively related to both self-efficacy and performance, as past research has shown the effect of peer modeling to be greater for “near peer” models (those that share similarities with the observer) (Bandura, 1986, Murphy, 1995). Finally, we examined students' ratings of the activity itself.

Results

The groups did not differ significantly in the proportion of females, $X^2(2) = 1.19$, $p = .55$, or the number of current answers students initially achieved in the intervention activity, $F(2, 160) = 1.405$, $PRE = 0.02$, $p = 0.25$. However, the groups did differ significantly in terms of total time spent on the intervention activity (seconds), $F(2, 156) = 130.2$, $PRE = 0.63$, $p < .001$. PRE, the Proportional Reduction in Error (see Judd et al., 2009), indicates how much error is eliminated by including the grouping variable in the model (PRE is also notated as η^2 in grouping models and equivalent to R^2 in a simple regression model). As expected, given the different requirements of the two conditions, students in the worked example group (M = 220.36, SD = 106.79) spent significantly less time on the feedback pages than students in the two dynamic video conditions (mastery: M = 1017.27, SD = 381.80; coping: M = 1066.75, SD = 362.80). Table 2 shows descriptive statistics for self-efficacy, quiz performance, perceived similarity to the peer model, and students' ratings of the learning activity across the three groups.

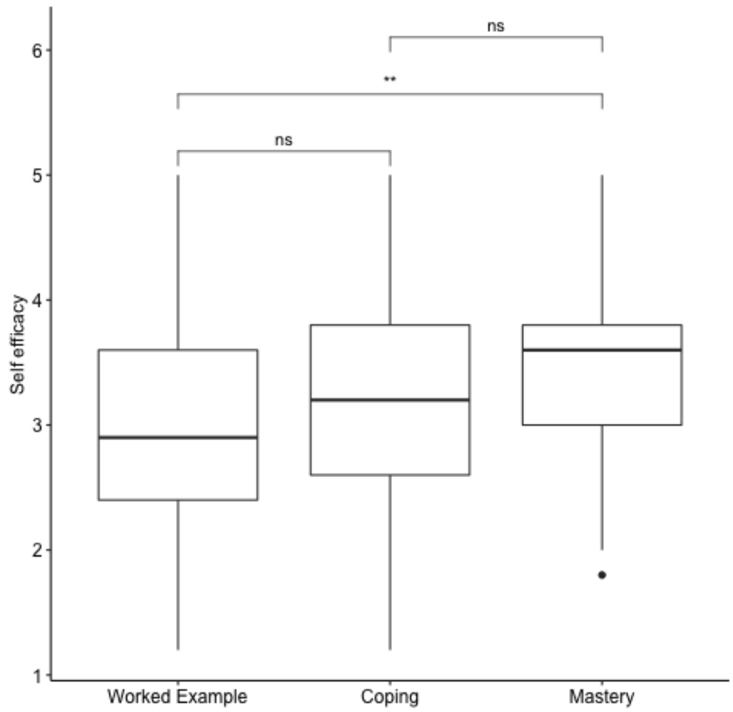
Table 2
Descriptive Statistics for Self-efficacy, Quiz Performance, Perceived Similarity, and Perceptions of the Learning Activity

Variable	**Condition**						**Overall**	
	Worked Example		**Coping**		**Mastery**			
	M	***SD***	***M***	***SD***	***M***	***SD***	***M***	***SD***
Self-efficacy	2.96	0.88	3.20	0.93	3.46	0.77	3.21	0.88
Quiz performance	87.65	11.45	86.53	17.90	93.21	7.15	89.12	13.08
Perceived similarity	2.82	0.76	2.75	0.80	3.04	0.73	2.87	0.77
Perceptions of the activity	6.08	0.84	5.67	1.35	5.85	1.05	5.88	1.10

Self-efficacy

A breakdown of self-efficacy scores across the three experimental conditions is shown in Figure 3. Results from a one-way ANOVA revealed a significant main effect of condition on self-efficacy, $F(2, 158) = 4.68$, $PRE = .06$, 95% CI[.01, .12], $p = .011$. A post-hoc Tukey test further revealed that students in the mastery condition (n = 54, M = 3.46, SD = 0.77) rated their self-efficacy significantly higher than students in the worked example condition (n = 56, M = 2.96, SD = 0.88), $p = .007$, $d = 0.54$, but not students in the coping condition (n = 51 , M = 3.20, *SD* = 0.93), *p* = .313, *d* = 0.26. Self-efficacy did not significantly differ for students in the coping and the worked example conditions, *p* = .275, *d* = 0.28.

Figure 3
Comparison of self-efficacy for students in the Worked Example, Coping, and Mastery conditions



Quiz Performance

Results from a one-way ANOVA revealed a significant effect of condition on quiz performance, $F(2, 158) = 4.104$, $p = .0183$. However, the effect size was small, *PRE* = .05, 95% CI[.00, .11]. A post-hoc Tukey test further revealed that students in the mastery condition (*M* = 93.21, *SE* = 1.76) performed significantly better than students in the coping condition (*M* = 86.53, *SE* = 2.52), *p* = .0238, *d* = 1.86, but not significantly better than students in the static worked example condition (*M* = 87.65, *SE* = 2.45), *p* = .0630, *d* = 1.55. Students in the coping condition did not differ significantly from students in the static worked example condition, *p* = .893, *d* = 0.31.

Perceived Similarity to the Peer Model

On average, students perceived the peer model to be somewhat similar to themselves (*M* = 2.87, *SD* = 0.77). The distribution of similarity ratings was roughly symmetrical with a median of 3 and a range of 4. Perceived similarity to the peer model did not differ significantly by condition ($F(2,159) = 2.09$, *PRE* = .03, *p* = .127); on average, students across the three conditions perceived themselves to be somewhat similar to the peer model.

To test whether students' perceptions of how similar they were to the peer model influenced self-efficacy and quiz performance, we fit separate linear regression models with perceived similarity as a predictor and self-efficacy and quiz performance as the outcomes. First, we fit a simple model with perceived similarity as the predictor for each of the two outcome variables. Next, we tested the effect of perceived self-efficacy on each outcome variable with condition as a categorical covariate. Finally, we tested the interactive effect of condition and perceived similarity on each of the two outcome variables to see if the effect of perceived similarity varied based on condition.

Results from the regression analyses for perceived similarity predicting self-efficacy are shown in Table 3. A simple regression revealed that similarity positively predicted self-efficacy ($F(1, 159) = 65.90$, $PRE = .29$, $p < .001$). Perceived similarity also positively predicted self-efficacy when condition was included in the model ($F(1,157) = 63.13$, $PRE = .29$, $p < .001$) suggesting that among students in the same condition, those who perceived themselves to be more similar to the peer model rated their self-efficacy higher. The interaction between condition and self-efficacy was not significant ($F(2, 1555) = 0.45$, $PRE = .01$, $p = .640$).

Table 3
Summary of Regression Analyses for Perceived Similarity Predicting Self-efficacy With and Without Condition as a Categorical Covariate

	B	***SE B***	**95% CI *B***		***t***	***p***
			2.5%	**97.5%**		
Simple regression						
Intercept	1.47	0.23	0.98	1.87	6.27	< .001
Perceived Similarity	0.62	0.08	0.47	0.77	8.12	< .001
Notes: $R^2 = 0.29$ (*ps* < .001)						
Model with condition as a covariate						
Intercept	1.25	0.24	0.79	1.72	5.32	< .001
Condition: Coping	0.29	0.14	0.01	0.57	2.05	.042
Condition: Mastery	0.37	0.14	0.10	0.65	2.66	.009

Perceived Similarity	0.61	0.08	0.45	0.76	7.95	< .001
Notes: R^2 = 0.31 (*ps* < .001)						

Results from the regression analyses for perceived similarity predicting quiz performance are shown in Table 4. A simple regression revealed that perceived similarity was positively related to quiz performance ($F(1,159) = 29.31$, *PRE* = .16, $p < .001$). On average, students who perceived themselves to be more similar to the peer model in the video performed better on the subsequent quiz. The effect of perceived similarity on quiz performance remained significant even when condition was included in the model ($F(1,157) = 142.59$, *PRE* = .14, $p <$ .001), suggesting that among students in the same condition, those who perceived themselves to be more similar to the model performed better on the subsequent quiz. The interaction between perceived similarity and condition (Model 6) was not significant ($F(2, 155) = 2.89$, *PRE* = .04, p = .059).

Table 4
Summary of Regression Analyses for Perceived Similarity Predicting Self-efficacy and Quiz Performance with Condition as a Categorical Covariate

	B	***SE B***	**95% CI *B***		***t***	***p***
			2.5%	**97.5%**		
Simple regression						
Intercept	69.84	3.69			18.94	< .001
Perceived Similarity	6.72	1.24			5.41	< .001
Notes: R^2 = .16 (*ps* < .001)						
Model with condition as a covariate						
Intercept	69.91	3.85	62.29	77.53	18.12	< .001
Condition: Coping	-0.62	2.30	-5.17	3.93	-0.27	.788
Condition: Mastery	4.23	2.29	-0.31	8.75	1.84	.068
Perceived Similarity	6.28	1.25	3.82	8.74	5.04	< .001
Notes: R^2 = .18 (*ps* < .001)						

Perceptions of the Activity

Overall, students rated the intervention activity highly. The distribution of composite activity ratings was left-skewed with a mean of 5.88, a median of 6, a standard deviation of 1.10 and a range of 6. Activity ratings did not differ significantly by condition, $F(2,159) = 1.90$, $PRE = .02$, $p = .153$; students in all three conditions reported positive perceptions of the activity, overall.

Discussion

In summary, students in the mastery condition performed significantly better than students in the coping condition on a delayed performance assessment but did not differ from students in the worked example condition. Additionally, students in the mastery condition, but not the coping condition, rated their self-efficacy significantly higher than students in the worked example condition. Across all three conditions, students who perceived themselves to be similar to the peer model on average, rated their self-efficacy higher and scored higher on the delayed performance test.

The results of this study add to the existing literature regarding the effectiveness of static and process feedback and provide preliminary insights into the potential benefits of integrating video-based feedback in online learning environments. In line with previous studies, we found that students benefited more from process feedback delivered through videos than from static feedback delivered through text. This is similar to the finding that students learn more from watching someone else code and debug errors than from writing code themselves and getting feedback on their responses (Raj et al., 2018).

This study also extends our understanding of *how* and *in what contexts* process feedback can be implemented to benefit learning. In the past, feedback in online learning environments has been limited to feedback about students' performance. This study contributes to a growing body of research investigating ways to deliver process feedback in online environments. But whereas most studies of process feedback in online environments focus on adaptive, text-based feedback, our research explores the potential of videos as a potential method for delivering process feedback online. One benefit of videos is that they convey richer, social information, which may benefit social-cognitive and motivational processes during learning. In contrast, text-based process feedback typically addresses cognitive and meta-cognitive processes alone.

Beyond extending our knowledge of process feedback, our results highlight how classical psychological insights about social learning might help us design more effective process feedback and instructional sequences. Though it is common to find educational videos with a knowledgeable instructor as the speaker, these videos were specifically designed to provide a peer model who could demonstrate a more realistic sequence of thinking and problem solving that the students could aspire to. By experimentally manipulating whether students saw a coping model or mastery model and measuring both cognitive and socio-emotional outcomes, we were able to see that the coping model was limited to socioemotional benefits while the mastery model led to both enhancing both types of outcomes.

Under some theoretical frameworks, modeling self-corrective behavior could have been *more* beneficial. However, the initial results of this study suggest that the coping model did not benefit self-efficacy or performance compared to a worked example, whereas the mastery model benefited both self-efficacy and future performance. These results are contrary to past findings that have shown no difference between mastery and coping models (e.g., Schunk & Hanson, 1989) and those that have found coping models to benefit learning more than mastery models (Schunk et al., 1987). What are the psychological processes that lead to the mastery condition having both the highest self-efficacy ratings and significantly higher delayed performance?

One possibility is that there may be differences in how higher-performing students engage with this feedback than lower-performing students. This sample was drawn from a highly competitive public university; would students from different institutions engage differently? We are currently pursuing data collection in other populations that make use of our data (e.g., community college, high schools) in the context of a broader approach to research and development in improving learning statistics, data science, and programming using R (e.g., Stigler et al., 2020).

Another possibility is that the mistakes modeled in the coping condition were too infrequent in this sample. Although these mistakes were chosen from *common* misunderstandings exhibited by prior students from the same introductory statistics course, the majority of students did not make the same errors. One future area of inquiry is whether matching feedback up with mistakes (e.g., if you made this error, click on this video) would be more effective than generally presenting a mistake-correcting model to students.

A third possibility is that students in our sample may benefit more from models that include only the correct responses. Though coping models have been shown to be beneficial in some contexts, they may be less useful in others. For example, in the context of interpersonal skills training, Baldwin (1992) compared the effect of observing only correct models and the effect of observing models that were correct sometimes and sometimes incorrect. They found that participants who observed the correct-only model performed better on the subsequent behavioral task than participants who observed the correct and incorrect model. Similarly, in a study that used both correct and incorrect worked examples to teach mathematics, Grobe & Renkl (2007) showed that students with more prior knowledge learned better from both correct and incorrect examples, whereas students with low prior knowledge benefitted only from correct examples. Most of the students in our sample had low prior knowledge for statistics and R programming, thus, it is possible they would have benefited more from a correct model than a model that demonstrated correct and incorrect responses (coping model).

The current study is only concerned with the modelling effect of peers. It does not examine potential differences between video-based feedback delivered by peers and feedback delivered by instructors. Therefore, an interesting topic for further studies to investigate is the effect of different types of video-based models on students' self-efficacy and performance. On one hand, literature suggests that peer-modelling may be potentially superior (Ledford & Wolery, 2015). On the other hand, if the modeled behavior is the essential part, we would suspect feedback depicted by a master instructor to be just as beneficial as a highly skilled peer. Furthermore, we did not account for differences in learners' backgrounds and how that may have influenced their perceptions of and interactions with the activity. Online learners are becoming increasingly diverse. Would a peer model representing a more traditional college-aged student be equally as effective for learners in a different age bracket? Our results provide evidence that students' perceptions of how similar they are to the peer model predict both self-efficacy and quiz performance. Thus, an important future direction is to investigate how students' form these perceptions, what factors they consider when making similarity judgements, and how individual student characteristics interact with features of the peer feedback to influence students' perceptions.

A limitation of this study and any video-based intervention is that we have no way to guarantee that students watched these videos. Although most students clicked on the videos and played them for a reasonable duration of time, some students in the video conditions may have engaged with the videos in less meaningful ways than others. Even so, it seems that either enough students watched the videos that we could detect the effect of them, or the effect was strong enough to overcome any noisy data from students who did not. Still, further research is required to examine whether students typically watch videos that are assigned in instructional settings. In follow-up studies, we plan to implement more effective ways of measuring whether students watched the videos, specifically, by pairing timestamp data from the online environment with a series of questions on the post-survey that asks students to indicate whether or not they skipped any of the videos, whether they changed the speed of the video playback, and whether or not they were multitasking while watching the videos.

Conclusion

The results of this study, although modest in scope, illustrate how the design of feedback could lead to noticeable differences in student learning even days after the intervention. This encourages us to consider how feedback functions in a longer course with presumably many more assignments and more opportunities for feedback. For example, in the online textbook *Statistics & Data Science: A Modeling Approach* (Son & Stigler, 2017–21), there are roughly 400 coding exercises. Currently, feedback on those exercises is based on outcomes (e.g., correct/incorrect) or look very much like the worked example condition (e.g., the correct code). Our results showed that showing brief peer modeling videos (just six experimental videos) in a single session led to changes in attitudes and learning detectable on a real class quiz. This spurs our research team to implement these changes in the context of our larger "better book" project to transform the way research-based improvements can impact many students and teachers (Stigler et al., 2020). The video feedback is a form that can be implemented in this textbook and our goal is to study the longer-term impact of improved feedback on a diverse array of student users (ranging from high school students who have not taken Algebra II yet to university students at a highly selective institution).

Instructors and instructional designers in many technology contexts have to make a decision on how to give feedback and simply showing students a correct worked response is an easy method of implementing feedback. Research such as ours gives them not only the motivation to give feedback differently but also suggest methods of implementing that feedback.

Feedback is a very small component of a whole course but because feedback happens frequently, a slightly better version of feedback may have recursive effects: small changes allowing students to learn a little better earlier may be able to act as a lever on later learning. Well-designed process feedback may be able to teach students how to learn and give them the confidence to persevere through it.

Declarations
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The authors asserted that ethics board approval was obtained from the University of California, Los Angeles for this study.

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