



## Improving Self-efficacy in Statistics: Role of Self-explanation & Feedback

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*Journal of Statistics Education* Volume 18, Number 3 (2010),  
[www.amstat.org/publications/jse/v18n3/hall.pdf](http://www.amstat.org/publications/jse/v18n3/hall.pdf)

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**Key Words:** Statistics problem solving; Self-efficacy; Self-explanation; On-line technology; Feedback; Pattern recognition.

### Abstract

Novice problem solvers often fail to recognize structural similarities between problems they know and a new problem because they are more concerned with the surface features rather than the structural features of the problem. The surface features are the story line of the problem whereas the structural features involve the relationships between objects in the problem. We used an online technology to investigate whether students' self-explanations and reception of feedback influenced recognition of similarities between surface features and structural features of statistical problems. On average students in our experimental group gave 12 comments in the form of self-explanation and peer feedback. Students in this Feedback group showed statistically significantly higher problem scores over the No-Feedback group; however, the mean self-efficacy scores were lower for both groups after the problem solving experiment. The incongruence in problem scores with self-efficacy scores was attributed to students' over-rating of their abilities prior to actually performing the tasks. This process of *calibration* was identified as an explanation for the statistically significant positive correlation between problem solving scores and post self efficacy scores for the Feedback group ( $p < .01$ ).

### 1. Introduction

Problem solving skills, according to [Bessant \(1992\)](#) and [Stangl \(2000\)](#), should be at the core of a statistics curriculum. [Bessant \(1992\)](#) points out that most students are taught many statistical procedures, but given a set of data, they usually face difficulties deciding which procedures to

use. For example, in introductory statistics courses students may be presented with a variety of word problems that require using procedures such as *t*-test, chi-squared test, or correlation. Although students may know how to use these kinds of statistical procedures, a major challenge is to learn when to use them given a new problem or a new data set.

Insufficient practice with a variety of problems ([Jonassen, Rebello, Wexler, Hrepic, and Triplett, 2007](#)) and low self-efficacy in statistics ([Onwuegbuzie & Wilson, 2003](#)) are two of the potential blocks students face when attempting to solve statistics problems. Statistics instructors commonly introduce new concepts by presenting definitions, associated concepts, theory, and derivations of the corresponding mathematical representations. Then they demonstrate how to solve a problem and often explicitly instruct students to perform certain procedures when solving word problems or implicitly cue them to carry out specific operations in the context of the lesson of the week ([Lovett and Greenhouse, 2000](#)). Students attempting to use this single-example approach are likely to ignore differences in the semantic and structural characteristics of the new problem. Novice problem solvers often fail to recognize structural similarities between problems they know and a new problem because they are more concerned with the surface features (story line) of the problem than with the structural features of the problem, which involve the relationships between the objects in the problem ([Mayer 1992](#)).

According to social cognitive theory ([Bandura, 1986/1997](#); [Pintrich & Schunk, 2002](#); [Schunk & Pajares, 2005](#)), students learn by observing others perform the same or similar tasks. This learning is affected by the reciprocal interactions between (a) personal factors in the form of cognitions and self-efficacy (perceived capabilities), (b) behaviors in the form of cognitive strategies such as providing feedback and self-explanations, and (c) environmental influences such as peer feedback, teacher feedback, and modeling. As students work on tasks and measure their successful progress toward learning goals, their self-efficacy for continued learning is enhanced and their motivation is influenced positively.

Self-efficacy beliefs are thoughts or ideas people hold about their abilities to perform those tasks necessary to achieve a desired outcome. These beliefs can influence people's behavior either positively or negatively based on their perception of their abilities concerning a particular task. Research has shown that epistemic beliefs affect how students approach learning tasks ([Schoenfeld, 1983](#)), monitor comprehension ([Schommer, Crouse, and Rhodes, 1992](#)), and create and carry out a plan for solving problems ([Schommer, 1990](#)). These researchers have provided empirical data on causal relationships and associations between self-efficacy and performance in subjects such as mathematics ([Schommer et al., 1992](#); [Pajares & Miller, 1994](#)). [Pajares and Miller \(1994\)](#) used path analysis to show the predictive and mediational role of self-efficacy in the area of mathematics. [Schommer \(1990\)](#) and [Schommer et al. \(1992\)](#) replicated the factor structure that belief in simple knowledge is negatively associated with comprehension and these beliefs predicted test performance. [Cleary \(2006\)](#) showed that the strategies students use in solving problems could be predicted based on their levels of self-efficacy. Students with higher self-efficacy used more effective learning strategies.

[Bandura \(1986\)](#) introduced vicarious experiences, or modeling, as one of the sources for developing self-efficacy beliefs by which individuals who are unsure of their abilities in a certain area have the opportunity to observe others similar to themselves perform the task. [Pintrich and](#)

[Schunk's \(2002\)](#) research indicated that students are capable of learning complex skills through observing modeled performances.

[Recker and Pirolli \(1995\)](#) modeled individual differences in students' learning strategies and found that self-explanation significantly affected students' initial understanding and their subsequent problem solving performance. [Chi \(1996\)](#) studied the effect of self-explanations in tutoring. Her study showed that tutor actions that prompt for collaborative construction of knowledge between tutor and tutee, such as prompting for self-explanation, may be the most beneficial in providing deep learning. Actions such as providing feedback could trigger learning partially due to removing students' misconceptions of the problems.

The online environment has been shown to provide a more productive setting for students to post written responses because it allows them to reflect more deeply on the materials and also increases the likelihood of participation for shy students or students who may feel uncomfortable talking with peers in a traditional classroom ([Everson & Garfield, 2008](#)). In our experiment, an online technology provided an authentic setting for students to collaborate and share knowledge in the form of self-explanation and peer feedback, which served as a modeling tool. The work of a student with a higher skill level served as a model or standard for less skilled students without creating undue pressure due to social comparison.

Guided by social cognitive theory, our study investigates the role of self-explanation and peer feedback on improving students' self-efficacy in the conceptual understanding of statistics problems. We focused specifically on three research questions: (a) Do self-explanations and peer feedback influence students' self-efficacy beliefs about solving statistics problems? (b) Do self-explanation and peer feedback impact students' pattern recognition in problem solving in terms of categorizing problems based on their structural and surface features? (c) Do feedback (self-explanation and peer feedback) and problem solving together impact self-efficacy?

## 2. Method

### 2.1 Variables

Students self-reported their demographic data consisting of age, gender, major, classification in college (freshman, sophomore, etc), and the number of math or statistics courses previously taken in college. To assess the social cognitive variables of self-efficacy in statistics problem solving, we measured the self-efficacy of both groups before and after the problem solving sessions. The No-Feedback group had only one set of problem scores; the Feedback group had pre and post problem scores. We chose to collect these data based on previous research on the impact of self and peer feedback in improving students' learning in the web-based environment ([Frederickson, Reed, and Clifford, 2005](#); [Lin, Liu, & Yuan, 2001](#); [Liu, Lin, Chiu, & Yuan, 2001](#); [Schunk & Pajares, 2002](#); [Wang & Lin, 2007](#); [Wigfield, Eccles, and Pintrich, 1996](#)). We also collected data on the number of comments, the change in problem scores, and the types of the self-explanation provided by the students in the Feedback group.

## 2.2 Participants and Setting

[Bandura \(1986\)](#) suggested that efficacy and performance be assessed together within as close a time period as possible and that efficacy assessment precede performance assessment. Therefore, in our experiment, we administered all four instruments within one class period of 50 minutes. This assessment process ensured that absences would not create a situation whereby some students completed one instrument but not another. Pilot testing demonstrated that one class period provided ample time in which to complete all assessment measures.

The participants in this study were one hundred thirty-eight (138) undergraduate students out of 142 students in two sections of a large business computing course at a university in the southeast United States. These participants represented three categories of majors: Business, Health Sciences, and Others. We informed the students that their participation in the experiment was voluntary and would result in the researcher evaluating how effectively students used feedback sources in the web environment to exchange their ideas and collectively solve problems. No remuneration for participation in the study was provided, but both instructors provided course credit for participation. Only four students declined to participate.

Participants were randomly assigned to either the Feedback or the No-Feedback group. As students arrived, they received a computer-generated random number, which assigned them to a computer in either the feedback or the no-feedback lab.

## 2.3 Experiment

The instruments were group administered in individual labs. Both groups completed the demographic and self-efficacy questionnaire first. Students in the No-Feedback group proceeded to solve three problems comprised of five sub-questions each. Students in the Feedback group were assigned randomly to groups of three to solve the same problems in a discussion forum environment using an interactive online system. Both groups completed the posttest efficacy measures in the last part of the survey. [Table 1](#) shows the design of the study.

**Table 1:** Schematic Representation of the Design of the Study

Group	Survey Pretest	Facilitate-Pro <sup>TM</sup> (Web Meeting Software) Solve Problems in Groups of Three	Problems	Survey Posttest
Feedback	X	X	X	X
No-Feedback	X		X	X

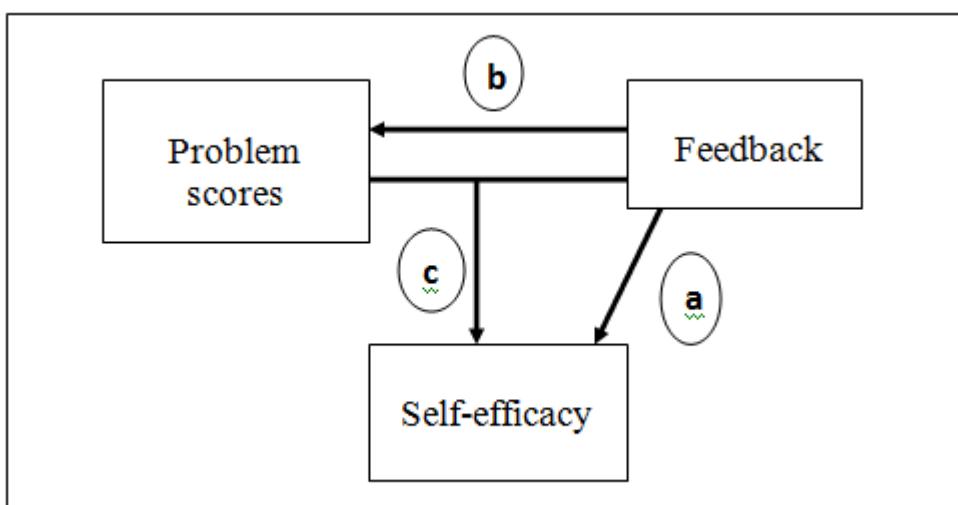
Students logged in with a number that was randomly generated. Their identities were kept anonymous from the researchers as well as from the other group members. With this technology students in the Feedback group worked collaboratively in groups of three where they gave and received feedback while answering the 15 questions. After the students had finished all of the problems as a group, each student solved the same problems on their own.

We used word problems that in the domain of introductory statistics are categorized into *t*-test, chi-squared test, and correlation problems (Quilici & Mayer, 1996). We did not use these terms, nor were students asked to conduct these tests. For each of the three word problems students answered five sub-questions: two questions tested students' surface understanding (story line) and three tested their understanding of the structure of the problems.

Students in the Feedback group chose one of the multiple choice answers and then provided a self-explanation, or rationale, for their choice. After each team member provided their responses, students could change their answers and/or provide additional feedback to the team members. Students demonstrated a surface understanding of the problem if they could recognize the dependent and independent variables using the story line. Students who recognized whether the independent variable in the problem involved one or two groups and whether the dependent variable was quantitative or categorical were deemed to have understood the structural features of the problem. For example, for the question in [Table 7](#), students who chose "average words typed per minute" as the response variable had correctly identified a surface feature of the problem. Students who identified that "average words typed per minute" was a quantitative variable had demonstrated structural understanding of the problem.

## 2.4 Research Questions

In order to test the self-efficacy theory and understand the relationship between self-efficacy beliefs, providing self-explanation, feedback and problem solving, we focused specifically on three research questions: (a) Do self-explanations and peer feedback influence students' self-efficacy beliefs about solving statistics problems? (b) Do self-explanation and peer feedback impact students' pattern recognition in problem solving in terms of categorizing problems based on their structural and surface features? (c) Do feedback (self-explanation and peer feedback) and problem solving together impact self-efficacy? The three models we tested are depicted in [Figure 1](#).



**Figure 1:** Hypothesized models of the relationships between Feedback, Problem Solving, and Self-Efficacy (a,b, and c represent questions of the study).

The experiment determined the influence of self-explanations and peer feedback on self-efficacy beliefs about solving statistics problems. In addition, it determined whether and how self-explanations and peer feedback influenced recognition of similarities between surface features and structural features of the problems we used in our study. The third question determined why and how both types of feedback and problem solving together influenced self-efficacy.

To answer the first question, we compared the differences in the self-efficacy scores for Feedback and No-Feedback groups controlling for the students' demographic variables. For the second question, we compared the mean of post problem scores for the Feedback group with the mean of problem scores for the No-Feedback group, again controlling for students' demographic variables. In addition, we analyzed with content analysis the Feedback group's rationale for the number and the kinds of self-explanation they provided, and we performed a correlation analysis between post problem scores and post-efficacy scores for both groups. For the third question, the differences in the students' self-efficacy scores were modeled as a linear function of the two explanatory variables—problem scores and group—as well as the students' demographic variables.

## 2.5 Instruments

**Instrument 1 (Demographic Variables):** Students were asked about their major, gender, age, and number of math or statistics courses previously taken in college. There were 40 women and 29 men in Feedback group with the mean age of 21.07 (SD = 5.98) years and mean number of previous math courses or statistics taken of 2.99 (SD = 1.85). There were 31 women and 38 men in No-Feedback group with the mean age of 20.55 (SD = 3.61) years and mean number of previous math courses or statistics taken of 3.07 (SD = 1.67). The age range was 17 to 57 for the Feedback group and 18 to 36 for No-Feedback group ([Tables 2 & 3](#)).

**Instrument 2 (Self-efficacy):** The first three items of the students' self-competence/confidence pretest and posttest in statistical problem solving, and in giving and receiving feedback, were from the [Frederickson et al. \(2005\)](#) study. The rest were added for this study. "How confident are you with solving statistical problems?" is a sample item to test respondents' efficacy in solving statistical problems. "How confident are you with peers detecting your errors?" is a sample item for efficacy about receiving and giving feedback. Item responses to this 10 item instrument (see [Appendix A](#)) were obtained on a 5-point Likert scale ranging from 1 (not at all confident) to 5 (very much confident). The instrument had a reliability coefficient of 0.92 in two pilot studies prior to this experiment. The reliability coefficient for the self-efficacy instrument increased from pre- to posttest for both groups: 0.80 to 0.88 for the Feedback group and 0.76 to 0.87 for the No-Feedback group. Reliability is a measure of internal consistency between test items. One common measure of test reliability is coefficient alpha by [Cronbach \(1951\)](#). The closer the Cronbach alpha is to one, the less error between true and observed scores.

Self-efficacy scores were the sum of the students' scores on 10 items shown in [Appendix A](#). The dependent variable representing self-efficacy in section 3.1 is the difference between students' pre and post self-efficacy scores. The descriptive statistics for the dependent variable self-efficacy is included in [Tables 2 & 3](#).

**Instrument 3 (Statistical Problem solving):** Students solved the three statistical problems shown in Display-1 (see [Appendix B](#)). For each problem they answered five sub-questions. These three problems shared a common set of surface features, or story line, in that each involved the experience of typists as the independent variable and typing speed as the dependent variable ([Quilici & Mayer, 1996](#)). The differences between the problems were in their structural features. These problems exemplify the surface and structural similarities common in examples in introductory statistics. Each correct answer received score of one, and incorrect answers received a zero—no partial credit was given. We used the sum of students' scores on 15 questions as the dependent variable *problem scores* in section 3.2. The maximum total problem score was 15.

## 2.6 Data Analysis

Statistical methods used were: summary statistics, one-way analysis of covariance (ANCOVA), correlational analysis, chi-squared test of independence, and content analysis. There were no missing data or extreme outliers. The assumptions of normality and equal variance for ANCOVA were met. The summary statistics for each group are presented in [Tables 2](#) (Feedback) and [3](#) (No-Feedback), respectively.

**Table 2:** Descriptive Scale Score Statistics Feedback Group (N=69).

Variable	Mean	Median	SD	Min.	Max.	Range
Pre Efficacy	33.22	33	5.37	19	48	29
Post Efficacy	30.51	30	7.42	10	50	40
y*	-2.71	-2	4.85	-14	7	21
Problem Scores	9.13	10	3.01	3	14	11
Age	21.07	20	5.98	17	57	40
Number of Courses	2.99	3	1.85	0	5	5

**Table 3:** Descriptive Scale Score Statistics No-Feedback Group (N=69).

Variable	Mean	Median	SD	Min.	Max.	Range
Pre Efficacy	34.39	34	5.39	22	46	24
Post Efficacy	31.94	32	7.11	10	46	36
y*	-2.45	-1	5.58	-22	14	36
Problem Scores	7.49	7	2.96	10	13	12
Age	20.55	20	3.61	18	36	18
Number of Courses	3.07	3	1.67	0	5	5

y\* is the difference in the post and pre- efficacy scores.

### 3. Results

#### 3.1 Efficacy

Did feedback during problem solving influence self-efficacy in problem solving?

We modeled the differences in the post and pretest efficacy scores ( $y_i$ ) as a linear function of method (F vs. NF), age, gender, number of math or statistics courses taken previously, and major (1). All the covariates were centered versus the mean. We classified majors into three categories Business, Health Sciences, and Others.

$$\begin{aligned}
 y_i &= (\text{post efficacy})_i - (\text{pre efficacy})_i \text{ for student } i, i = 1, \dots, 138. \\
 y_i &= \beta_0 + \beta_1 * \text{method}_i + \beta_2 * \text{age}_i + \beta_3 * \text{gender}_i + \beta_4 * \text{course}_i \\
 &\quad + \beta_5 * \text{Business}_i + \beta_6 * \text{Health}_i + \beta_7 * \text{Other}_i + \varepsilon_i \\
 \varepsilon_i &\sim N(0, \sigma^2) \text{ was random error associated with the } i^{\text{th}} \text{ student.}
 \end{aligned} \tag{1}$$

The mean of self-efficacy scores for the Feedback group at pretest was 33.22 (SD=5.37) and at posttest 30.51 (SD=7.42). For the No-Feedback group, the mean at pretest was 34.39 (SD=5.39) and at posttest 31.94 (SD=7.11). These results show a decrease in the mean of self-efficacy from pre-to posttest for both groups.

We performed a one-way analysis of covariance for model (equation 1). The variable method was not a significant predictor of the differences in post and pretest self-efficacy scores ( $R^2$ -squared =.06). Age (p-value=.03) was the only predictor with moderate statistical significance. The interaction effects between independent variables were not significant.

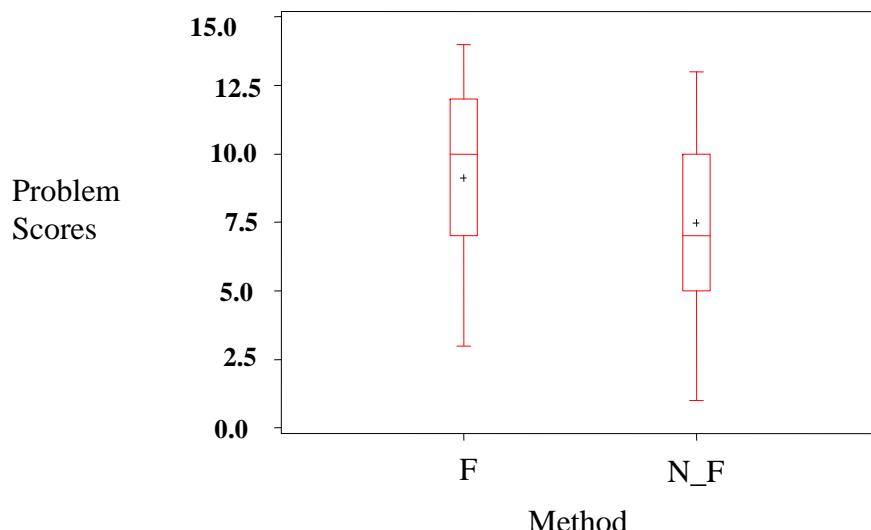
#### 3.2 Problem Solving

Did feedback influence problem solving scores controlling for covariates?

We modeled the final problem scores as a linear function of method (F vs. NF), age, gender, number of math or statistics courses taken previously and major as shown in (equation 2). All the covariates were centered versus the mean.

$$\begin{aligned}
 &\text{for student } i, i = 1, \dots, 138; \\
 &\text{problem\_scores}_i = \beta_0 + \beta_1 * \text{method}_i + \beta_2 * \text{age}_i + \beta_3 * \text{gender}_i + \\
 &\quad \beta_4 * \text{course}_i + \beta_5 * \text{Business}_i + \beta_6 * \text{Health}_i + \beta_7 * \text{Other}_i + \varepsilon_i \\
 &\varepsilon_i \sim N(0, \sigma^2) \text{ was random error associated with the } i^{\text{th}} \text{ student.}
 \end{aligned} \tag{2}$$

The mean problem score was 9.13 with a standard deviation of 3.01 for the Feedback group and 7.49 with a standard deviation of 2.96 for the No-Feedback group ([Tables 2 & 3](#)). The box plots comparing the distribution of the scores of two groups are shown in [Figure 2](#). There were no outliers in these data. The mean of the problem scores was higher for the Feedback group; however, both groups had similar standard deviations around the mean.



**Figure 2:** Comparison of the problem scores for two groups (Feedback, No-Feedback)

Results of the ANCOVA indicated that method ( $p$ -value = .0008) and number of courses taken in statistics ( $p$ -value = .0011) were statistically significant predictors of problem scores ( $R^2$  = .16). [Table 4](#) was created to further understand the association between feedback and problem scores by comparing the proportions of students in both groups who scored a passing grade of at least a D or better. In the Feedback group, 59% of the students (41/69) scored at least D or better compared to 37% in the No-Feedback group ( $\chi^2$  = 6.53,  $df=1$ ,  $p < .05$ ).

**Table 4:** Frequency Distribution of Group by Scores

Group	Problem scores		Total
	$\geq D$	< D	
Feedback	41	28	69
No-Feedback	26	43	69
Total	67	71	138

### 3.3 Self-efficacy & Problem solving

Did feedback and problem solving together impact self-efficacy?

The differences in the post and pretest efficacy scores ( $y_i$ ) were modeled as a linear function of method (F vs. NF), problem scores, age, gender, number of math or statistics courses taken previously, and major ([equation 3](#)).

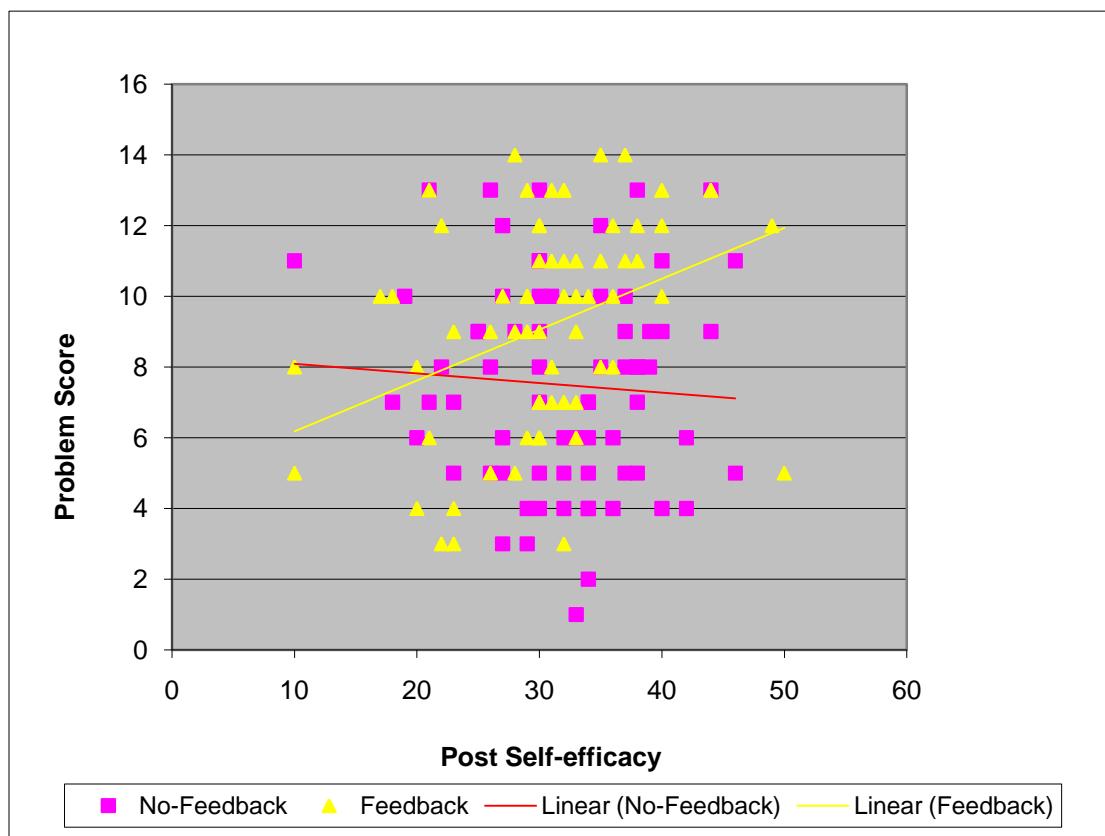
$y_i = (\text{post efficacy})_i - (\text{pre efficacy})_i$  for student  $i$ ,  $i = 1, \dots, 138$ .

$$y_i = \beta_0 + \beta_1 * \text{method}_i + \beta_2 * \text{problem\_score}_i + \beta_3 * \text{age}_i + \beta_4 * \text{gender}_i + \beta_5 * \text{course}_i + \beta_6 * \text{Business}_i + \beta_7 * \text{Health}_i + \beta_8 * \text{Other}_i + \varepsilon_i \quad (3)$$

$\varepsilon_i \sim N(0, \sigma^2)$  was random error associated with the  $i^{\text{th}}$  student.

We performed a one-way analysis of covariance for model (equation 3). Neither method nor problem scores were statistically significant predictors. Age (p-value = .04) was the only statistically significant covariate.

We also examined the correlation between changes in self-efficacy scores and problem scores as well as the correlation between the post efficacy scores and problem scores for both groups. The differences in efficacy scores  $y_i$  were positively correlated with problem scores for the Feedback group and the Pearson coefficient was statistically significant ( $r = .33, p = .005$ ). For the No-Feedback group, this relationship was not statistically significant. The posttest self-efficacy scores for the Feedback group correlated positively with their problem scores and this association was statistically significant ( $r = .36, p = .003$ ). This relationship for the No-Feedback group was not statistically significant. The scatter plot in Figure 3 shows the relationship between problem scores and post efficacy scores for both groups.



**Figure 3:** Correlation between Post Self-efficacy and Problem Scores for two groups (Feedback, No-Feedback)

### 3.4 Analysis of Qualitative data for Problem Solving

#### 3.4.1 Correlational study

Students' comments in the Feedback group to each other were analyzed in terms of quantity of comments and kinds of self-explanations. We conducted a correlational study to determine whether students' post self-efficacy score and problem scores correlated with the number of comments students provided, their age, and number of math or statistics courses taken previously. Table 5 contains the descriptive statistics used in the content analysis.

**Table 5:** Descriptive Scale Score Statistics for Content Analysis for Feedback Group (N=69).

Variable	Mean	Median	SD	Min.	Max.	Range
Number of Comments	12.16	12	3.23	6	20	14
Age	21.10	20	5.98	17	57	40
Number of Courses	2.99	3	1.85	0	5	5
Post efficacy	30.51	30	7.42	10	50	40
Problem scores	9.13	10	3.01	3	14	11

[Table 6](#) shows Pearson correlation coefficients between students' problem scores, the number of comments they provided, age, number of previous math or statistics courses, and post efficacy scores. The Pearson correlation coefficients were statistically significant between number of comments and problem scores ( $r = .74, p <.05$ ) and post-efficacy scores ( $r = .19, p <.05$ ). The number of comments did not have a significant correlation with number of previous math or statistics courses or with age.

**Table 6:** Pearson Correlation Coefficients between Problem scores, Comments, Age, Number of Math Courses Taken, and Post Self-efficacy Scores

	1	2	3	4	5
1. Problem scores	-				
2. Comments	0.74*	-			
3. Age	-0.13	-0.04	-		
4. Number of Courses	0.25*	0.07	0.03	-	
5. Post Efficacy	0.36*	0.19	-0.23	0.02	-

\*  $p <.05$

The mean number of feedback comments was 12.16 ([Table 5](#)). On average the feedback sessions were 15 minutes long. In this experiment, on average students provided 0.8 comments per minute or 48 comments per hour compared to 0.11 questions students ask in a classroom setting in an hour as reported by [Chi \(1996\)](#). Therefore, students in the Feedback group in this experiment had many more opportunities to provide self-explanations and evaluate peer feedback than students in ordinary classrooms.

#### 3.4.2 Surface versus structural similarities

Students' self-explanations were analyzed with content analysis to determine how students sorted the critical features of the problems' structure, which were to recognize whether the independent variable involved one or two groups and whether the dependent variable was

quantitative or categorical. We employed content analysis, a qualitative data analysis methodology ([Creswell & Plano Clark, 2007](#)), to analyze students' comments in the Feedback group to each other in terms of quantity and kinds of self-explanation. Cognitive studies of analogical problem solving, or thinking by analogy, involves the three processes of recognition, mapping, and abstraction ([Quilici & Mayer, 1996](#)). In this experiment, the focus was on recognition. Students sorted each problem based on the story line of the problem, i.e., they solved the problems based on the shared attributes of the objects in the problem ([Quilici & Mayer, 1996](#)). Then they solved based on the structure, meaning the shared relations among objects, e.g., problems involving *t*-tests involve two independent groups as the independent variable and a quantitative measure as the dependent variable. We then read students' rationale to determine how their explanation described the characteristics of the independent and dependent variables.

These problems involved *t*-tests, chi-squared tests, and correlation analysis; however, these terminologies were not used, nor were students asked to conduct any tests. We wanted to know if, for instance, students chose "average words per minute" as the response variable to a question in regard to the surface features of the problem, and if they would be able to correctly identify the scale measurement of "average words per minute" as a quantitative variable in the structure question.

[Table 7](#) illustrates one student's response to a question. The elaboration provided by this student contained key words that drew similarities between the objects of the story. This student first defined the question in her own words; and then matched the key word from the story to her newly defined phrase to answer the question. [Liu, Lin, Chiu, & Yuan \(2001\)](#) showed that technology that provided an environment for students to record their reflection had a significant impact on their learning. This recording of reflection or students' self-explanation served as a model for other students in the group ([Bandura, 1997](#)). [Pintrich and Schunk's \(2002\)](#) research indicate that students are capable of learning complex skills through observing modeled performances. In our study, self-explanation served as a modeling tool. The work of a student with a higher skill served as a model or standard for less skilled students without creating undue pressure due to social comparison.

It was quite likely that one student's self-explanation helped remove a misconception for another student in the group ([Chi, 1996](#)). The technology used for the discussion forum in this study allowed the instructor to monitor students' responses. However, during this experiment no intervention was made as to avoid introducing biases in the results.

**Table 7: Example of Questions and One Student's Feedback**

A personnel expert wishes to determine whether experienced typists are able to type faster than inexperienced typists. Twenty experienced typists (i.e., with 5 or more years of experience) and 20 inexperienced typists (i.e., with less than 5 years of experience) are given a typing test. Each typist's average number of words typed per minute is recorded.

A response variable measures the outcome of a study.

In this problem the response variable is:

- A. experience
- B. 5 years
- C. average number of words typed per minute
- D. twenty experienced typists

One student wrote: "It's C because the response variable is something that is the result of the project, the avg. words per min is what tells us who are the better typers."

The content analysis revealed that students who provided elaborations for each question such as the example shown in [Table 7](#) achieved a higher mean in their post problem scores than those who did not engage in self-explaining. The results here were consistent with the reported proportions in [Table 4](#) and correlations in [Table 6](#).

#### 4. Discussion

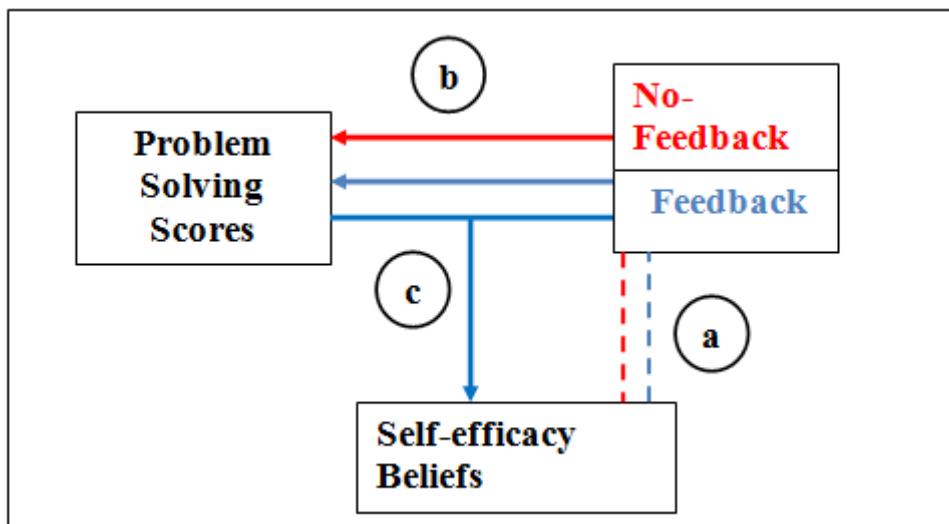
In this study we examined strategies that improve self-efficacy in problem solving processes. These strategies involved students solving statistics word problems by comparing the target problem with a source problem based on structural similarities rather than surface similarities. They used online technology as a medium to write self-explanations and provide feedback to each other. Our study tested the theoretical prediction that self-efficacy is enhanced by feedback that fosters problem solving skills. This prediction is based on social cognitive theory which posits reciprocal interactions between behaviors, cognitions, and environmental variables ([Bandura, 1986](#)). Using social cognitive theory as a framework, we examined the changes in students' efficacy beliefs (personal factor) as they solved statistics problems (cognition) and provided feedback and self-explanation (behavioral factor) in an online technology (environmental factor).

Our research questions were: (a) Did self-explanations and peer feedback influence students' self-efficacy beliefs about solving statistics problems? (b) Did self-explanation and peer feedback impact students' pattern recognition in problem solving in terms of categorizing problems based on their structural and surface features? (c) Did feedback (self-explanation and peer feedback) and improved problem solving together impact self-efficacy?

To answer these questions, we collected quantitative data, including self-efficacy scores and problem solving scores, for two groups of students in a feedback and a no-feedback setting. We also collected qualitative data, such as students' self-explanation about the problem steps and peer feedback. Students' self-explanations and feedback were analyzed with content analysis to

determine the extent of strategies involving self-explanation and peer feedback they used to solve the problems.

The result for question (a) was that there was no relationship between self-efficacy scores and group (Feedback vs. No-Feedback). The result for question (b) was that problem scores were significantly different between groups. The Feedback group had higher average problem scores than the No-Feedback group. For question (c), problem scores positively correlated with self-efficacy scores only for the Feedback group. For part (a) we anticipated the differences in self-efficacy scores to be significantly different for the Feedback group vs. No-Feedback group. However, the theoretical framework of the study indicates that for feedback and self-explanation to improve pattern recognition and influence self-efficacy beliefs significantly, the outcome of the performance must be sustained; meaning students must exhibit the skill of solving problems based on structure similarities consistently. Therefore, the solving of problems using feedback sessions needs to be repeated for students to raise their problem solving scores. [Figure 4](#) is the schematic representation of the results.



**Figure 4:** Schematic Representation of the Results (a, b, and c represent questions of the study). Solid lines represent statistically significant relationships between the variables, with blue corresponding to the Feedback group and red to the No-Feedback group.

The findings in this study support the social cognitive theoretical prediction that feedback can impact self-efficacy positively when students are provided with real time evaluation, assessment indicators, and progress indicators to convey to students the results of their efforts. In this experiment it was not feasible to use assessment tools to provide students with real time evaluation. Therefore, a technology that allows providing real time feedback would be necessary for future replication of the experiment.

Students in the Feedback group showed a statistically significant gain in their overall problem scores over the No-Feedback group ([Tables 2 & 3](#)); however, the mean efficacy scores were

lower for both groups after the problem solving experiment ([Tables 2 & 3](#)). This incongruence between self-efficacy beliefs and actual performances has been reported in previous studies ([Schunk & Pajares, 2002](#)) and can be attributed to students' lack of understanding of what they do not know before they take the test ([Chi, 1996](#)) or to students not fully understanding what is required to execute a task successfully. However, it is shown in [Schunk and Pajares \(2002, 2005\)](#) that as students gain experience in problem solving, their assessment of their capabilities improves. Feedback allowed students to match their problem solving performance in statistics to their actual level of self-efficacy in the statistics. This process of acquiring experience to match performance in a task with existing level of self-efficacy in that task is called calibration.

The students in the Feedback group solved the problems first in a group setting, then individually with no feedback. On each step of the problems the students observed others similar to themselves provide self-explanation and feedback. This process allowed students who were unsure of solving the problems based on structural similarities rather than surface similarities to read and learn from peers' reasoning and feedback. For the Feedback group, problem scores were positively correlated with post self-efficacy scores and also with the change in self-efficacy scores. The Pearson correlation coefficients between each of these variable pairs were statistically significant ([section 3.3](#)). However, for the No-Feedback group, these correlations were not statistically significant. [Bandura \(1986\)](#) showed that learning from modeling and observation from group members is using vicarious experiences to shape one's beliefs. The feedback environment in our experiment was a medium for students to improve self-efficacy in problem solving. One of the limitations of this study is that the No-Feedback group only solved the problems once.

Self-explanations may have served as a reason for the higher overall problem scores for the Feedback group because feedback from some students may have helped remove misconceptions for the others. In addition, self-explanation and receiving feedback is similar to providing and receiving feedback between tutee and tutor. [Chi \(1996\)](#) showed that the tutee's self-explanation served as an effective means of learning because the tutor learned the tutee's misconceptions. In addition, the pattern of dialogue developed as a result of self-explanation and receiving feedback and the interaction between the students allowed tutees to be more active in their learning.

In our study, the number of comments in the form of self-explanation that students in the Feedback group made was positively correlated with their problem scores. Examination of the qualitative data showed that the average number of comments for students in the Feedback group whose problem scores were grade D or higher was above the mean number of comments 12.16 ([Table 5](#)).

In this study, the students in the Feedback group interacted much more often than students in classrooms. On average, these students had the opportunity to provide self-explanation or feedback comments more often than classroom students ([Chi, 1996](#)). According to [Chi \(1996\)](#), a higher degree of communication among members of a group promotes collaborative construction of the knowledge.

Both groups were instructed to solve multiple statistical problems by comparing each problem with a given definition based on the surface and structure similarities. Our results are consistent

with one of our hypotheses that students with low self-efficacy toward statistics problem solving who are exposed to instruction which emphasizes solving problems based on structure and who provide self-explanation are more likely to improve their problem scores than similar students who are not exposed to providing explanation and feedback. However, the brief exposure to examples emphasizing structure without supporting guidance or instruction does not yield a lasting effect ([Quilici & Mayer, 1996](#)). Therefore, the problem solving sessions with feedback need to be replicated over a period of time to improve students' performance in categorizing problems based on understanding of the underlying structure.

The analysis of the contents of the self-explanations that students provided for each question indicated that those who provided more thoughtful responses and elaborated on the rationale for their choices showed higher gains in problem scores from pre- to posttest than did those who gave fewer comments or did not elaborate on their responses.

The students' gain in problem solving in the Feedback group is in agreement with [Clark and Mayer's \(2003\)](#) research on the impact of collaborative learning on the web and its impact on problem solving skills. Clark and Mayer emphasize the process of practice using collaboration on the web in learning and effectively using metacognitive strategies of planning, monitoring, regulating, and integrating to become successful in problem solving. According to Clark and Mayer, when instruction allows students to reflect more deeply on the steps of problem solving, they are more likely to use metacognitive strategies. Therefore, the Feedback group's gain in average problem solving scores may be attributed to the effect of giving or receiving feedback or to the effect of practice in solving statistical problems.

The content analysis of students' choices and their rationale revealed the misconceptions students had and the knowledge pieces they lacked while sorting the similarities between surface features and structural features in the statistical problems. In the Feedback group, 28 students who scored less than grade D ([Table 4](#)) generally did not pay attention to the nature of two structural features of the problems: whether the independent variable involved one or two independent groups and whether the dependent variable was quantitative or categorical. Their descriptions of quantitative and categorical types showed they did not have a firm grasp of their differences and their meanings. These students scored correctly on the surface questions of these problems but not on the structure questions. In addition, they were more confused about classifying the correlation problem based on its structure than they were on the other two types of problems. The problem regarding correlation involved comparing two variables for one group (see [Appendix B](#)). An instructional implication that warrants further study is that students would benefit from instruction and practice in identifying and describing the characteristics of the independent and dependent variables in elementary statistics word problems.

Improvements could be made to enhance the reliability of constructs to enhance the reliability of measures. For example, if self-efficacy measurements were improved, the change from pre- to posttest may become a significant predictor in the impact of feedback on problem solving between two methods of learning.

In summary, this study examined the effectiveness of web-based instruction in statistics problem solving from a social cognitive perspective. The reciprocal nature of the variables in social

cognitive theory makes it possible for teaching and learning efforts to be directed at personal, environmental, or behavioral factors ([Pajares, 2002](#)). Using social cognitive theory as a framework, instructors can work to improve students' low efficacy beliefs (personal factor) about a subject such as statistics or about learning in an on-line environment. They can improve students' academic skills (behavioral factor) by providing them with efficient models and feedback. Those who construct web-based learning systems can alter technology (environmental factor) that may undermine student success and design learning systems that accommodate learners' needs.

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## Appendix A

## Instrument 2: Students' Perceived confidence/competence (self-efficacy-pre and post)<sup>1</sup>

Response scale [to be applied to each part of each question]:

1                    2                    3                    4                    5

1. How confident are you with solving statistical problems?
2. How well do you feel you are understanding statistical problems?
3. How competently could you apply statistics in practice?
4. How confident are you with inspecting peers' work and posting feedback?
5. How confident are you with detecting your errors?
6. How confident are you with peers detecting your errors?
7. How confident are you with peers commenting on your work?
8. How confident are you with incorporating peers' comments in your work?
9. How confident are you with peers correcting your work?
10. How confident are you with the teacher correcting your work?

<sup>1</sup> The first three items were from Frederickson et al. (2005) study, the rest were added for this study. The instrument had a reliability coefficient of 0.92 in two pilot studies prior to this experiment.

## Appendix B

### Display-1

(1) A personnel expert wishes to determine whether experienced typists are able to type faster than inexperienced typists. Twenty experienced typists (i.e., with 5 or more years of experience) and 20 inexperienced typists (i.e., with less than 5 years of experience) are given a typing test. Each typist's average number of words typed per minute is recorded.

(2) A personnel expert wishes to determine whether or not experienced typists are likely to be fast typists and inexperienced typists are more likely to be slow typists. Twenty experienced typists (i.e., with 5 or more years of experience) and 20 inexperienced typists (i.e., with less than 5 years of experience) are given a typing test. Based on the test, each typist is classified as fast or slow.

(3) A personnel expert wishes to determine whether typing experience goes with faster typing speeds. Forty typists are asked to report how many years they have worked as typists and are given a typing test to determine their average number of words typed per minute.

### Display-2

Questions were structured as shown below: first, the problem, then a short description and then the question.

A personnel expert wishes to determine whether experienced typists are able to type faster than inexperienced typists. Twenty experienced typists (i.e., with 5 or more years of experience) and 20 inexperienced typists (i.e., with less than 5 years of experience) are given a typing test. Each typist's average number of words typed per minute is recorded.

A response variable measures the outcome of a study.

In this problem the response variable is:

- A. experience
- B. 5 years
- C. average number of words typed per minute
- D. twenty experienced typists

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