Multiple Submissions and their Impact on the 'Path of Learning'

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Abstract

Learning theory from the 'behaviorist' camp suggests that a stimulus (problem) with quick feedback and then repetition (resubmission) will increase student learning. To test this assumption an experiment was conducted. In an introductory management information system class students are given the opportunity to submit several skill-building assignments prior to the due date. These submissions were graded promptly with feedback provided and the students could then re-submit the assignment for final grading upon the actual due date. Data that was collected from 159 students on three different spreadsheet and database assignments indicates that there is a relationship between the choice of a student to take advantage of pre-grading and the final test grade that tests similar skills as in the assignments. However, the relationship is not immediate, but it appears that students need to follow a 'path of learning' in order to achieve a higher level of understanding, whereby prompt and constructive feedback can play an important role.

Keywords: pedagogy, learning theory, feedback, computer literacy

1. INTRODUCTION

As introductory class size increase and more classes move to the web or a blended delivery method, building more learning options independent of the instructor are needed. Instructors have moved from the 'Sage on the Stage' to instructors who need to guide the student to self-directed learning opportunities. (King, 1993 and Jones 1999)

A particular challenge for instructors of introductory computer literacy courses is to provide the appropriate level of hands-on skill assignments with clear feedback and then an opportunity for the students to learn from their errors. However, students often only receive a grade and some minor comments as a feedback, and no option is given to correct the errors and actually learn from the mistakes.

Learning theory suggests that increased learning will occur with additional stimuli and responses (Gagne, Briggs and Wager, 1992). Even though there are several studies in pedagogy and psychology discipline addressing this argument, they fail to address validity of this theory in teaching skills.

This study investigates the results on 'learning' of providing students the opportunity to submit their assignments (spreadsheet or database) in advance of the due date (pre-grading). They then receive a high level of feedback and are given the option to re-submit an updated assignment prior to the final due date. The researchers felt that if students could actually 'correct' their errors and not move on to the next assignment or concept then learning from feedback might occur. In the current paper, we address the following research question: **Does pre-grading followed by prompt feedback support student learning?**

To answer the research question, we first provide an overview of the relevant literature on learning. We then describe our experiment, analyze and discuss the data that we collected, and draw a number of conclusions.

2. BACKGROUND / LITERATURE REVIEW

A student's success is influenced by the ability of the educator to present new information and to evaluate the students' understanding of the information. This process requires the student to learn the material covered by the educator.

Based on behavioral learning theory, Gagne et al. (1992) proposed several design principles for effective instructional design courses , including contiguity, repetition, and feedback. Contiguity is the concept that the **feedback** should follow the **response** without delay. The longer the delay of the feedback to a learning stimulus the less is the likelihood of correct answers to future similar questions. The second principle of repetition states that practice strengthens learning and improves a learner's retention. Gagne et al.'s (1992) conceptual framework of cognitive learning includes nine "conditions for learning":

- Gaining attention ("reception")
- Informing learners of the objective ("expectancy")
- Stimulating recall of prior learning ("retrieval")
- Presenting the stimulus ("selective perception")
- Providing learning guidance ("semantic encoding")
- Eliciting performance ("responding")
- Providing feedback ("reinforcement")
- Assessing performance ("retrieval")
- Enhancing retention and transfer (generalization")

The results of subsequent research studies suggested that eliciting performance and practice from the student ("responding") and providing adequate feedback ("reinforcement") are the events most directly connected to student success (Martin, Klein & Sullivan, 2007).

Murray (1998) encouraged a teaching style based on drill/rote learning and memorization. Modules should be built with many exercises that are example driven. The principle of feedback requires that instructors inform the learner about whether the answer was correct or incorrect. In the case of an incorrect answer, feedback should include a new path to solve the problem. This new path could be a hint at the correct answer, a restatement of a prior fact, or even a new example that is less complicated (Uden & Beaumont, 2006). In addition, feedback that indicates that the answer is correct is just as important as feedback on incorrect answers.

Orientation and recall is defined as a process where learning involves the synthesis of prior information that must be recalled to short term memory (Uden & Beaumont, 2006). Similarly, there is a school of thought that learners construct knowledge by making sense of experiences in terms of what is already known (Eugenia, 2010).

"Responding" is required from learners after they have been given sufficient material to comprehend an objective (Tomei, 2008). Performance on the student's part is required when practice is included in a lesson. This form of practice implies an active response to the material provided.

For example, in a database lesson, "responding" might require a student to create a query that will count the number of records in a table in order to demonstrate his/her comprehension of this newly introduced concept.

Responding enables the student to reinforce his/her understanding. Effective practice should parallel the assessments that will be used to test skills and the knowledge reflected in an objective (Reiser & Dick, 1996).

This study extends the Gagne et al. (1992) study showing response and reinforcement as the key learning components to investigate whether hands-on skills could be taught more effectively focusing on these key components.

The knowledge gained from this study provides valuable insight for instructors, particularly those teaching online web-based courses.

3. EXPERIMENTAL DESIGN

For the experiment, we collected data in five sections of an introductory information systems course that included a number of computer literacy assignments and that were taught by two different instructors. Students were given the option to submit a number of skill-building assignments prior to the due date for pre-grading. Each assignment represented a new concept or advanced computer skill that was introduced in class prior to the assignment, as follows:

1. Create a database with queries and multiple relationships between tables, using Microsoft **Access**;
2. Create a spreadsheet with multiple scenarios, using Microsoft Excel **Scenario Manager**;
3. Create a spreadsheet looking for an optimal solution, using Microsoft Excel **Solver**.

Following the optional pre-grading, (re-submission) and the final grading of each project assignment, the learned skills were tested during a hands-on portion of an exam later in the semester. Figure 1 details the steps completed for each skill concept, whereby the shaded areas and bold text refer to data points that we recorded for the current study.

For the research model (Figure 2), we use the grade on the hands-on test as the main dependent variable and representing the level of understanding that a student has achieved with respect to a certain skill at the end of the course module. While we did not administer an entry-level test to assess a student's initial level of knowledge, we assume that the grade in the

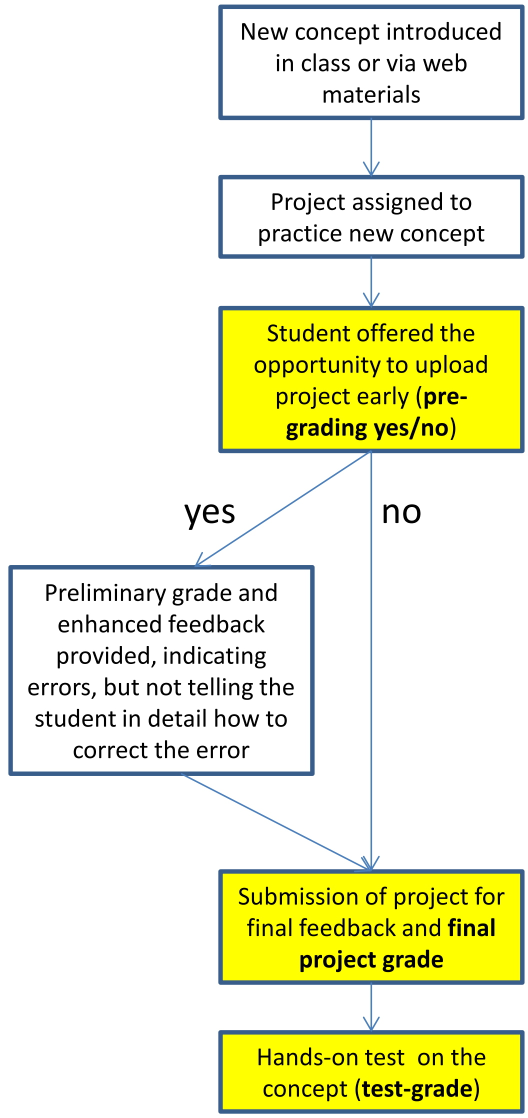

Figure 1: Teaching and Grading Process (Experiment setup)

hands-on test is a good indicator for the extent to which a student who completes the course possesses the skills and knowledge that the course was intended to provide. In order to address our research question and to assess to what extend pre-grading can indeed enhance learning, and thus lead to a higher level of understanding, we wanted to find out whether there is a statistically significant link between pre-grading (yes/no) and the result of the hands-on test. In addition, we were also interested in the role of the final project grade as an intermediary step toward the hands-on test. Consequently, we analyze our data to test the following three hypotheses:

H1: Pre-grading (yes vs. no) is associated positively with the final project grade.
H2: The final project grade is associated positively with the grade in the hands-on test.
H3: Pre-grading (yes vs. no) is associated positively with the grade in the hands-on test.

In order to account for systematic differences between sections and instructors, we also include the instructor as a control variable in the model (Figure 2).

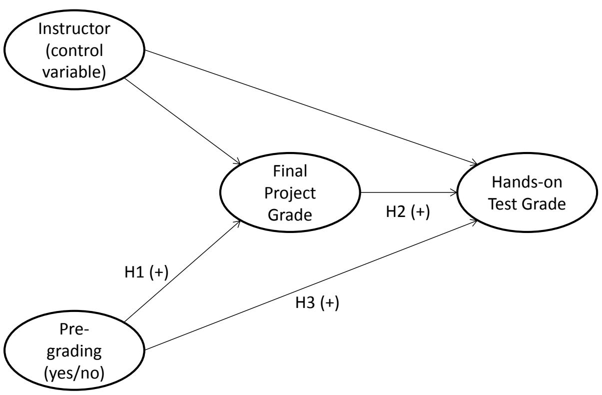

Figure 2: Research Model

4. DATA ANALYSIS

Data were collected from 159 undergraduate students in an introductory information systems course who were assigned three computer literacy assignments (Access, Scenario Manager, and Solver). The students represent a total of five sections in Fall 2010 and Spring 2011 that were taught by two instructors. One session was taught online, all other sessions were taught in the classroom. For each student, the collected data indicated (1) whether the student had taken the opportunity of pre-grading (yes/no) for a particular assignment; (2) the final project grade; and (3) the grade in the associated hands-on test. To account for individual differences in teaching style, course structure, and details on projects, tests and grading schemes, we controlled for the instructor as a fourth variable in our analysis. The differences between the sessions of an individual instructor were not included in the analysis as these tend to be smaller than the differences between individual instructors (an assumption that was also confirmed by additional data analyses not reported here).

Each dataset from n=159 students pertained to a particular skill concept (Access, Scenario Manager and Solver), and was analyzed separately. A descriptive summary of the data is provided in the appendix. Student participation in the pre-grading option ranged from 29% to 83%.

Data analysis was performed using the structural equation modeling (SEM) approach with WarpPLS 2.0 software that applies the partial least squares (PLS) technique (http://www.scriptwarp.com/warppls). SEM is a second generation statistical method that, in contrast to regression, allows for the simultaneous assessment of multiple independent and dependent constructs, including multi-step paths (Gefen, Straub, & Boudreau 2000). PLS was considered an appropriate method to test the research model because there is a broad agreement among scholars that PLS is well suited for exploratory research and theory development (in contrast to theory testing), which is the case in the current research study. Given that all of the variables in the research model included only one indicator, it was not necessary to assess the validity of latent variables. Instead, we could immediately proceed to test our hypotheses with the structural model.

As is indicated in Figures 3 to 5, we found very similar results for all of the three skill concepts of Access (Figure 3), Scenario Manager (Figure 4), and Solver (Figure 5). In all three datasets, H1 and H2 were confirmed at high levels of statistical significance ($p<.001$), whereas H3 was confirmed only once at a 4%-level of statistical significance.

Project 1: Access

For the first data set (Access) the model fit with the data was very good to acceptable at the 10% level:

- Average Path Coefficient (APC)=0.191, P=< 0.001
- Average R-Squared (ARS)=0.201, P=0.081
- Average Variance Inflation Factor (AVIF) =1.069, Good if < 5

We found H1 and H2 to be supported with highly significant paths between pre-grading (yes/no) and project grade, and between project grade and final grade. It is this combination of the two paths (1) pre-grading/project grade, and (2) project grade/test grade that we refer to as the 'path of learning' in the reminder of the paper. H3 was not supported. The paths between instructor and the grades for the project and test were weak and/or not significant (Figure 3).

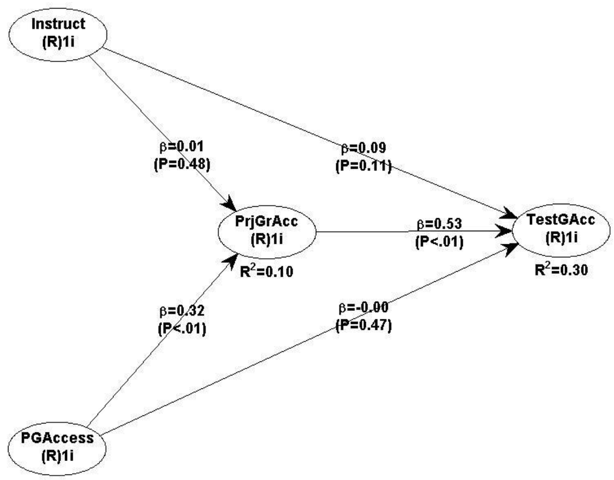

Figure 3: Results for Project 1: Access

Project 2: Scenario Manager

For the second dataset (Scenario Manager), the model fit with the data was very good:

- APC=0.190, P=<0.001
- ARS=0.122, P=0.019
- AVIF=1.071, Good if < 5

We found that H1, H2 and H3 were all supported with statistically significant paths, plus we noted a marginally significant path between instructor and grade for the project (5%). Still, the strongest links in terms of Beta-coefficients and significance levels again occurred along the 'path of learning' between pre-grading and project grade, and between project grade and test grade. While we recorded a marginally significant association between instructor and project grade for the scenario manager data set, the association between instructor and the test grade was not statistically significant (Figure 4).

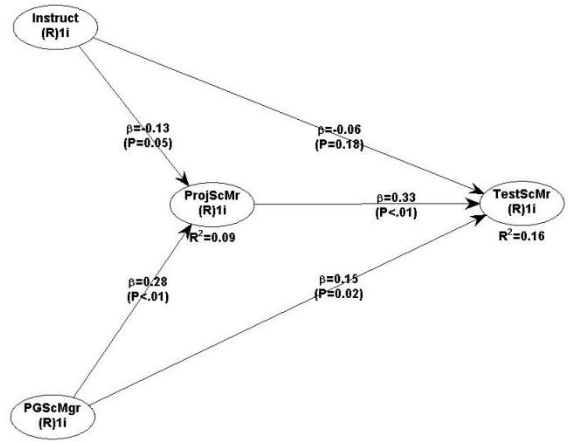

Figure 4: Results for Project 2: Scenario Manager

Project 3: Solver

For the third dataset (Solver) the model fit with the data set was also very good:

- APC=0.222, P=<0.001
- ARS=0.265, P=<0.001
- AVIF=1.085, Good if < 5

Again, we observed the path of learning in the form of strong support for H1 and H2, whereas H3 was not supported. The associations between instructor on the one hand, and project and test grades on the other hand were near zero and/or insignificant (Figure 5).

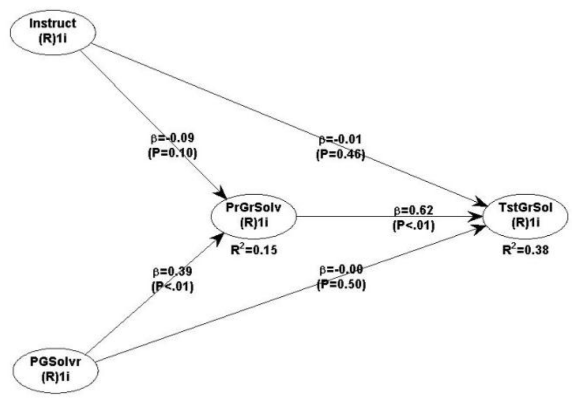

Figure 5: Results for Project 3: Solver

5. DISCUSSION

In all three of our data sets, we found strong positive associations between pre-grading (yes vs. no) and final project grade (H1) and between final project grade and test grade (H2). The direct associations between pre-grading (yes vs. no) and the test grade were much weaker if they were statistically significant at all (H3).

Our data indicates strong support for the 'path of learning' between pre-grading, project grade, and test grade independent of assignment, instructor, and number of students who participated in pre-grading. We also note that the path of learning appears to require two steps and cannot be shortened. Students who submitted an assignment for pre-grading were as such not more (or less) likely to achieve a good grade in the hands-on test than students who did not take this opportunity (and vice versa).

It appears that students need to take the feedback that is provided in the pre-grading comments serious, and that they subsequently have to make an effort to submit a high-quality project for a good final project score. It is this intermediate step of learning that – according to our data – is associated most closely with a higher grade in the concluding hands-on test, thus, signaling a higher level of understanding and learning.

Two additional issues warrant discussion. First, we wonder about the role of the instructor. At the beginning of the semester, the two instructors who participated in the experiment coordinated their skills assignments and hands-on tests to some degree to ensure structural comparability of the resulting data. Both instructors also used the same online system for grading (Matthews and Janicki, 2010). Despite these interactions, however, a number of differences remained, for example regarding the structure of the syllabus, individual teaching styles, project and test instructions, and grading schemes. The format of delivery also varied as one of the five sections was taught online. Despite all of these differences, our data shows a limited role of the individual instructor on the strength and significance of the path of learning. And, while we found some limited statistical evidence for a link between instructor and project grades, the – more important – associations between instructor and test grades (signaling learning) were even weaker with Beta-coefficients near zero and/or inacceptable significance levels.

Another issue to consider is whether we are witnessing a situation where the smarter students were the ones who primarily took advantage of the path of learning. Unfortunately, we did not have the opportunity to collect data on previous skills and the knowledge that students brought into the course, or on their overall grade level averages. However, we were surprised to find such clear and statistically strong associations, both in terms of Beta-coefficients and significance levels, between pre-grading (a choice made by the students), and the grades for projects and tests. Given the lack of statistical evidence that pre-grading alone resulted in high test scores we suggest our data to indicate that learning occurs along a pre-defined path, largely independent of a student's previous knowledge. While we cannot answer the question of whether 'smarter' students benefitted more (or less) from pre-grading than students that were less smart, we found pre-grading to play an important role along the path of learning. We suggest that it may be up to the individual instructor to encourage all students in a session to take the opportunity for pre-grading (followed by efforts to submit a high-quality final project), given its critical role as part of the learning process.

6. CONCLUSIONS AND OUTLOOK

In the current paper, we set out to address the research question of whether pre-grading followed by prompt feedback can support student learning. Based on the data that we collected for three different skills that were part of an introductory information systems course taught by two different instructors, we suggest the following answer to our question: Yes, pre-grading can support student learning, as long as a student takes the feedback from pre-grading seriously and makes an effort to subsequently submit a high-quality project.

Pre-grading alone does not seem to guarantee learning, as measured by hands-on test results, but pre-grading can help to increase the likelihood of a student submitting a high-quality project as part of the learning process. We suggest that our data provides evidence for a path of learning that includes three elements: (1) early submission of a project for pre-grading and prompt feedback; (2) preparation of a high quality project based on the early feedback for final project submission; (3) preparation for hands-on test based on feedback on the final project. Each step along the path is important to help a student learn and achieve a high level of understanding (test grade).

Before we conclude the paper, a couple of limitations and avenues for future research should be pointed out. As mentioned above, our study is limited in its ability to determine exactly how much learning has occurred during the course, mainly because of the fact that skills were not assessed prior to the course. This also means that we have not addressed in detail how learning actually occurs along the identified path of learning, and what factors may be particularly helpful in addition to pre-grading. While the focus of the current study was on the general role of pre-grading as part of the learning process, a better understanding of what actually happens along the path of learning should be considered an important extension of our work. In order to help instructors better structure their courses, it would be beneficial to have a deep understanding about what types of learners pre-grading can best support, as well as what groups of students are most prone to follow he suggested path of learning.

Another extension of our study could be to extend the path of learning to additional assignments and projects. In some cases, more than one assignment might be given in relation with a certain topic. It would be interesting to see to what extent the path of learning could be traced between assignments, which could again be helpful for course structuring and course management.

Lastly, it will be important to explore the boundary conditions of our findings and determine generalizability. While the results of our analysis are very comparable for the two instructors who participated in the current study, the question remains, what factors in particular contributed to the similarity of the outcomes, and what factors might in fact help obscure or obstruct the path of learning. Just like students learn in many different ways, instructors have many different approaches to teaching. Future research might also want to assess the applicability of the path of learning to other types of assignments, students and learning environments. The path of learning appeared to be very clear in the current study, but we also need to understand its limitations in order to move forward in our continued quest to help students learn.

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Appendix

Descriptive Statistics:

Section	Instructor	Assignment (1: Access; 2: Scen Mgr; 3: Solver)	N (number of students)	Pre-Grading (yes vs. no)		Project-Grade (out of 100)	Test-Grade (out of 100)
1	1	1	36	83%	Min:	0.00	1.00
					Max:	100.00	100.00
					Average:	95.94	94.28
					Standard Deviation:	16.68	17.15
2	1	1	34	44%	Min:	0.00	0.00
					Max:	100.00	100.00
					Average:	88.21	89.50
					Standard Deviation:	29.67	28.45
3	2	1	33	55%	Min:	42.50	91.00
					Max:	100.00	100.00
					Average:	89.14	97.48
					Standard Deviation:	12.76	2.02
4	2	1	28	50%	Min:	62.60	89.00
					Max:	100.00	100.00
					Average:	92.64	97.29
					Standard Deviation:	9.88	2.94
5	2	1	28	32%	Min:	43.70	75.00
					Max:	100.00	100.00
					Average:	89.87	96.14
					Standard Deviation:	12.89	5.79
1	1	2	36	58%	Min:	0.00	0.00
					Max:	100.00	100.00
					Average:	89.89	85.06
					Standard Deviation:	17.79	28.10
2	1	2	34	29%	Min:	0.00	0.00
					Max:	100.00	100.00
					Average:	76.12	70.62
					Standard Deviation:	33.57	40.83
3	2	2	33	70%	Min:	5.00	0.00
					Max:	105.00	98.00
					Average:	81.76	73.21
					Standard Deviation:	28.65	32.38
4	2	2	28	50%	Min:	5.00	3.00
					Max:	105.00	100.00
					Average:	83.18	71.92
					Standard Deviation:	27.38	29.99
5	2	2	28	64%	Min:	0.00	1.00
					Max:	105.00	98.00
					Average:	69.14	82.46

					Standard Deviation:	38.17	21.17
1	1	3	36	73%	Min:	0.00	0.00
					Max:	100.00	100.00
					Average:	91.11	94.28
					Standard Deviation:	23.24	16.80
2	1	3	34	41%	Min:	0.00	0.00
					Max:	100.00	100.00
					Average:	78.82	73.76
					Standard Deviation:	37.93	31.99
3	2	3	33	82%	Min:	0.00	0.00
					Max:	100.00	100.00
					Average:	89.09	85.58
					Standard Deviation:	20.22	24.04
4	2	3	28	79%	Min:	0.00	0.00
					Max:	100.00	100.00
					Average:	81.50	84.18
					Standard Deviation:	26.97	22.84
5	2	3	28	68%	Min:	0.00	23.00
					Max:	100.00	100.00
					Average:	81.25	88.21
					Standard Deviation:	28.79	18.70