

# CAN UNDERGRADUATES LEARN PROGRAMMING WITH A “VIRTUAL PROFESSOR”? FINDINGS FROM A PILOT IMPLEMENTATION OF A BLENDED INSTRUCTIONAL STRATEGY

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## Abstract

This study presents the main findings from *the pilot implementation* of a blended instructional strategy in one section of a multi-section course of introduction to programming with C++. The implemented strategy blended pre-recorded online lectures and homework assignments, with one weekly optional face-to-face meeting. The same instructor taught both the blended instruction and the traditional face-to-face lecture. The focus of this study was twofold: a) determine potential negative impact of the blended format, and b) identify the major predictors of final performance in this course. A one-way ANOVA analysis indicated no statistically significant differences in final course score between the control and the treatment groups. The analysis of a proposed path analysis model showed that self-efficacy, perceived engagement and perceived difficulty are significant predictors of students' final performance in the course.

## Introduction

The development of digital media has made possible many varying and innovative delivery systems and instructional methodologies for university courses. The motivations for developing fully online or blended courses are many. Some of the motivating factors are tied to the learners' needs while others are linked to organizational and social factors [1].

## *Addressing Learner Needs*

A first need that online and blended instructional formats address is *extended access*. The traditional student life does not work for all those seeking to learn. The “non-traditional student” includes older students wishing to resume an abandoned college career, employed people wishing to continue an education, students with family commitments that prevent living on campus, and professionals trying to refine and upgrade existing skills. In addition, there are students who have limiting medical conditions that would prevent “normal” enrollment as well as students from one university who may need or want to enroll in a course provided by another institution. In each of these cases, online delivery of instruction could mitigate the problem.

A second motivational factor linked to learner needs is the possibility to engage in *self-paced learning*. A limiting factor in the face-to-face, classroom-based instructional mode is that the instructor must teach to the norm. The downside of this approach is that slower learners are often overrun while faster learners can get bored. Using digital media available online allows students to pace themselves to suit their individual needs.

## *Organizational and Social Factors*

In Missouri, the governor urges institutions of higher learning to use the digital media revolution to deliver educational content to make more efficient use of the limited

government support for education. Along with addressing this governmental mandate, using online and blended course materials can allow the university to leverage instructional resources so as to significantly reduce the overhead of teaching more students in a better way.

Enrollment at many universities is up, and in computer science enrollment is skyrocketing. Therefore, while state funding is down, universities must serve a larger student body. Developing online course materials is a first step in addressing these contradictory issues.

## **Instructional Context**

### ***The Target Courses***

The instructional material in this project was developed for two introductory programming course pairs, a lecture course and an accompanying lab. These pairs of courses work together to teach students the basics of programming and problem solving using C++. The first pair of courses (CS 053/054) is typically targeting first-year students in computer science or computer and electrical engineering, while the second pair of courses (CS 074/078) is targeting students in all other engineering disciplines. This second pair of courses (CS74/78) covers a subset of the material covered in the first pair (CS53/54); students enrolled in them will take no further computer science coursework. The first pair of courses is the focus of this study.

The syntax of the language C++ is factual and straightforward to teach. Problem solving techniques are much more difficult to imbue. Thus, the design of these course pairs is to have a weekly lab exercise that is relatively easy and made to familiarize the students with the syntax of the language, while the programming exercises of the lecture course are much more difficult and include extensive programs designed to cultivate problem solving techniques and ideas. In this way, students should not be stumbling over questions of syntax when using the computer language to

code their algorithms for the larger problems and therefore their efforts would be spent on solving the problem.

For CS 053/054, the two courses' instructors meet weekly to coordinate instruction in two ways: 1) to insure that all students in all sections have the same materials presented in like manner and at the same time, and 2) to coordinate the topics of the lab exercises to reflect the current topics in the lectures. So doing, all students will have seen the same material presented prior to starting the lab exercise. CS 053 is a traditional lecture course. The first lecture is used to set the stage for the rest of the semester by going over the syllabus, how programs are submitted, and so on. All other lectures are dedicated to explaining the C++ language, with the focus on its syntax and functionality. Grades are determined by three regular exams and a final exam, along with 10 major programming assignments. Each day's lecture time allows for students to ask questions about any of the material presented, or about the programming assignment that is currently due.

Students are expected to learn not only the syntax of C++, but also how to apply its constructs to write programs that solve problems. In CS 054, upon entering the computer lab each student has to solve a lab exercise (a link to a web posting for the problem) created by the instructor that coordinates the lab section. The lab instructor will sometimes give a mini-lecture on some aspect of the concepts required to complete the lab, usually as a review of the lectures in CS 053. Two hours are given to complete the required program, and students submit their work electronically for grading. During lab time, students may ask for help of the instructor or of the two upperclassmen who are paid to assist the instructor.

### ***A New Paradigm***

Following current findings regarding the benefits of blended instruction [19], the decision was made to test a pilot implementation of how the CS53/54 pair of courses would work as a

blended offer with all lecture material being available online via public access while the lab course would require physical presence on campus. The lecture material is offered as open-access web-based instructional software and could be accessed via a direct link, or through course management system, such as Blackboard.

For this pilot implementation one section of CS 053 had the three normal weekly lecture meetings replaced with the blended offer. In addition, the section in the blended format included one weekly one-hour meeting. In our pilot implementation for one section in CS 053, the instructor had chosen to only strongly encourage attendance on this day rather than requiring the attendance. These sessions were utilized for questions and answers as well as review of the most important topics covered in the online lecture material assigned for that week. On the Friday before each week, the instructor sent an email to the class to remind students of the online lectures assigned for the coming week. In our trial run, we found however that very few questions were asked during these weekly meetings. Thus, for much of the time in these face-to-face weekly meetings the instructor reviewed and highlighted important lecture topics. The face-to-face meeting day for the section enrolled in the blended format was also used for the exams throughout the semester.

In every other way, the blended-format section of the course was handled as other sections were. There were no special sections of CS 054, the lab course, and therefore the face-to-face lab blended section students were mixed with students from traditional sections of CS 053.

### ***Development of the Materials***

The lecture material for this pilot implementation was developed a year before its initial use. As a first preparing step, the instructor transcribed the lecture materials for each class meeting into Word documents. Typically this was done on the same day that the

lecture was delivered in the corresponding traditional face-to-face meeting. These documents were then converted into HTML files adhering to a template-like format designed for ease of use. This format also followed accessibility guidelines ( <http://diveintoaccessibility.info/>).

The essential information in each lecture was then used as the basis for a set of PowerPoint slides demonstrating the principles associated with each topic. Then, using a screen capture program, the instructor created short voice-over videos to complement the lecture material presented in the text format. Markups and callouts were used to enhance learner's experience by replicating as close as possible the teacher presenting in a face-to-face meeting. Each video recording was then transcribed for closed captioning by the Educational Technology staff. The lectures are YouTube searchable also.

To conclude, each lecture has its own webpage with a complete index for the course to the right-hand side, a video presentation, downloadable slides both in PowerPoint and pdf formats, and a written transcription. Overall for the course there are approximately 1250 slides for the 53 lecture modules and they can be freely accessed online at <http://classes.mst.edu/compsci53/>.

### **Research Goals**

Considering the exploratory nature of this *pilot implementation*, the first goal of this study was to identify and test a predictive model that will link students' perceptions with their final performance in the course. The main motivation behind this first research goal was to identify monitoring factors that have the potential to help predicting students' performance throughout the semester.

The second goal was to use the identified model to test if the new instructional strategy that blended online lecture materials with face-to-face application activities has the potential to harm students' performance. This goal was also

driven by the need to understand students' response to the introduction of online instructional strategies in an environment built on a face-to-face educational culture.

## Research Methodology

### *Proposed Research Model*

To move beyond the overall analysis we looked for a research model that links predictive variables derived from students' self-reported measures to students' instructional performance. We decided to use self-reported measures for both students' entry level and their performance for three major reasons.

First, the use of the online modules that was the subject of our study *was a pilot implementation* and we tried to introduce it with minimal disturbances to the instructional process. Second, the self-reported measures used in this study are less intrusive than the traditional knowledge-based tests and therefore better suited as monitoring tools for future implementations of this model. Finally, research in educational fields shows that self-efficacy, the major self-reported measure used in this study, is a major predictor for students' performance outcomes. Self-efficacy has been defined as an important step toward a unifying theory of behavioral change [3]. It determines the level of effort learners will extend in future activities and the degree to which this effort will be sustained when learners will face obstacles and challenging experiences such as those associated with e-Learning [14]. That is, learners with high self-efficacy will participate in a given task more readily, will work harder, and persist longer when they encounter difficulties. In educational settings, self-efficacy has also proved to be a good predictor of students' learning and motivation in subsequent tasks [14, 17]. The information used to appraise self-efficacy resides in past and current performance, and the feedback associated with these performances. In addition, students' success has proved to increase self-efficacy while failure has proved to decrease it [17].

Self-efficacy was also found to have a complex mediating relationship with the learning antecedents and learning outcomes [4]. However, when the focus was on using online learning and tutoring modules, the results in the research literature were mixed. For example, in an engineering course where e-learning modules were used, self-efficacy showed a significant low to medium positive correlation with students' learning but was not a significant predictor of post-test scores [8]. In another study, where students used web-based worked examples, self-efficacy did not mediate between the use of web-based modules and achievement as predicted. It rather served as a complementary measure of learning performance predicted by the students' use of web-based worked examples [9].

Theoretical and empirical analyses of major determinants of self-efficacy in both educational and work-training environments found both internal and external determinants of self-efficacy. Of these, *motivation and task complexity* have proved to be significant determinants of self-efficacy [10, 18]. Students' *motivation* in relation to the performed instructional task proved to have a positive relationship with self-efficacy, while *task complexity* proved to have a negative relationship to self-efficacy. To increase the predictive power of perceived motivation, for this study we decided to use perceived engagement, a measure that combines perceived motivation and elements of perceived usefulness [5].

If perceived engagement is an internal factor influenced by students' perception of the overall instructional environment, task complexity has both an external and an internal characteristic. Along with clear external factors such as complexity of instructional components, dynamic aspects and level of informational cues [20], task complexity also has an internal aspect due to students' perception of the components. This internal perception of task complexity results from the interaction between the external

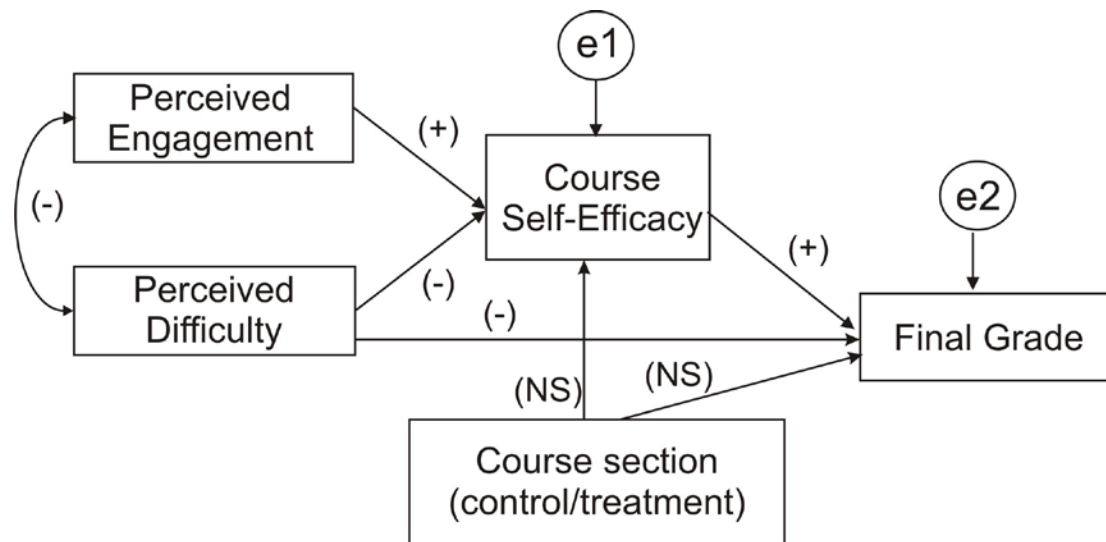


Figure 1. Proposed Path Analysis Model.

factors of task complexity and students' experiences with the same, or similar, types of tasks [11, 18]. Because self-efficacy and motivation are both self-reported measures, we decided to use perceived difficulty as a proxy for measuring task complexity in our model. The proposed path analysis model that builds on the discussed predictors of students' performance is presented in Figure 1.

As suggested by previous research, perceived engagement is predicted to have a positive correlation (+) with self-efficacy, while perceived difficulty is predicted to have a negative correlation (-) with both self-efficacy and final grade. In addition, following the reported research in this area [10] self-efficacy is predicted to have a partial mediating role between perceived difficulty and final grade and therefore is predicted to have a positive correlation (+) with performance outcomes.

The model also shows the measurement errors, e1 and e2, associated with the two endogenous variables, self-efficacy and performance outcome, respectively. Finally, because we used a quasi-experiment in which we compared the performance of one regular face-to-face lecture section (control) with the performance of one online lecture section (treatment), we introduced a control variable with two levels (1 – control and 2 – treatment). Since the instructional

materials and the associated assessment tasks were similar for both sections, we predicted that there would be no significant impact of this last variable on both self-efficacy and final grade.

### ***Procedure and Research Instruments***

For the purpose of this study we followed two sections of the same course taught by the same instructor. The first section used a traditional face-to-face lecture while the second one was engaged in the new blended format where the lecture was offered fully online and complemented with one optional weekly face-to-face discussion meeting. We administered online an entry and exit survey, with students' participation in both of them being voluntary and rewarded with bonus points.

***Entry Survey.*** Because students were not randomly assigned in the two sections that were the focus of this study, we administered an entry survey to measure several factors used as a benchmark to test the homogeneity of the two groups.

The entry survey was administered online during the first week of the course using the course management system, Blackboard. However, because as indicated in the description of the proposed research model described above, *this was a pilot*

*implementation* of these online modules we decided to use a series of self-reported measures for the homogeneity of the two groups. Since the two sections of students (taught by the same instructor) we engaged in this study were part of six-sections of this course the self-reported measures were found *less intrusive to implement* than the traditional pre-test measures typically used for this type of benchmark. In addition, the major measures of students' exit performance was also a self-reported measure and therefore comparable with the entry benchmarks used in this pilot implementation. For the entry survey we used three previously validated scales.

The first one was an academic efficacy scale [12, 13]. The scale has five self-efficacy statements and uses a five-point Likert evaluation scale (1-Totally Disagree to 5-Totally Agree). For our dataset Cronbach's alpha, the internal reliability measure, was .74, a value above .70, the accepted indicator of a good internal reliability for a scale. The next two scales used were engagement and difficulty of the course introduced with a statement to reflect the fact that the scales are targeting expectation measurements (*...you expect this course to be*). These two scales were made of six and respectively four semantic-differential items using a nine-point evaluation scale with 1 representing low and 9 representing high levels of the factor measured with each scale [5]. The internal reliability measured with Cronbach's alpha was .88 for the expected motivation scale and .87 for the expected difficulty scale, both values above .70, the accepted indicator of a good internal reliability for a scale. The fourth scale used in the entry survey was a self-efficacy with online learning scale [2]. The scale has five statements and uses a five-point Likert evaluation scale (1-Totally Disagree to 5-Totally Agree). The internal reliability measured with Cronbach's alpha was .90, a value clearly above .70, the accepted indicator of a good internal reliability for a scale.

**Exit Survey.** The exit survey was administered during the last week of the course. As with the entry survey, we used Blackboard, the course

management system, to administer online the exit survey. The exit survey included the same motivation and difficulty scales used in the entry survey with a slight rewording of the introductory statement to reflect that this is a perception rather than an expectation measurement (*...this course was*). To increase the sensitivity of the measure for self-efficacy we administered both the academic efficacy scale used in the entry survey and a second self-efficacy scale validated in the educational research literature [15]. This second scale has nine self-efficacy statements and uses a five-point Likert evaluation scale (1-Totally Disagree to 5-Totally Agree). We then used exploratory factor analysis to identify the stronger mix of items from the two scales. The first factor identified with this procedure included all five academic efficacy items and two items from the second self-efficacy scale. This first factor explained 34% of the total variance explained by both scales and its internal reliability measured with Cronbach's alpha was .87, higher than .79, the internal reliability value for the five academic efficacy items used in the entry survey. Therefore we used this factor to generate a new scale and called it *course self-efficacy*. The resulted *course self-efficacy scale* is presented in the Appendix. This new scale was used in the exit analyses associated with this study.

### **Participants**

Participants in *this pilot study* were first-year students in computer science or computer and electrical engineering. The entire course had three face-to-face lecture sections and one blended-format with online lecture section.

Of these, one face-to-face lecture section with 33 students and the blended-format with online lecture section with 15 students taught by the same instructor were engaged in this pilot study. The participation was voluntary and rewarded with bonus points. A total number of 39 students participated in both entry and exit surveys, of which 29 were enrolled in the

Table 1. Homogeneity of Students' Characteristics.

Variable		Basic Statistics					
		1	2	3	4	M	SD
1.	Academic Efficacy (1-5)	-	.29	-.27	.61**	4.34	.63
2.	Expected engagement (1-9)		-	.34*	.38*	6.67	1.33
3.	Expected difficulty (1-9)			-	-.28	5.46	1.33
4.	Online self-efficacy (1-5)				-	3.74	.87

Notes: \*  $p < .05$  (2-tailed); \*\*  $p < .01$  (2-tailed)

traditional face-to-face lecture and 10 were enrolled in the blended version that offered online lecture modules complemented with the optional weekly face-to-face discussion meetings.

As previously described in the procedures section, to test the homogeneity of the two groups at the entry point, we used three self-reported variables that targeted common factors expected to be similar for both groups: academic efficacy, expected engagement and expected difficulty. In addition we used an online self-efficacy scale to test for potential entry-level disadvantages associated with the online format of the lectures for the blended-instruction group. Table 1 summarizes the basic statistics for the variables used to analyze group homogeneity at the beginning of the course.

A one-way ANOVA analysis for each of the three common entry variables, academic efficacy, expected engagement and expected difficulty indicated that there was no statistically significant difference between the two groups, traditional and blended format. Therefore, at the entry point the students enrolled in the two sections of the course were homogeneous.

In addition, a one-way ANOVA analysis for the online self-efficacy indicated that the mean online self-efficacy for the traditional group ( $M_{\text{traditional}} = 3.58$ ,  $SD = .87$ ) was significantly lower than the mean online self-efficacy for the online group ( $M_{\text{online}} = 4.20$ ,  $SD = .71$ ),  $F(1, 38) = 4.14$ ,  $p < .05$ . This finding indicates that, at least from this perspective, at the entry point the

group engaged in the blended format that used online lecture modules was not facing a handicap linked to the nature of the instructional processes analyzed in this study.

### Results and Interpretation

Path analysis, a form of Structural Equation Modeling (SEM), allows for specifying a priori, for inferential purposes, the relation between students' final grade, course self-efficacy and two of its major determinants, perceived engagement and difficulty [6]. The cases/parameter ratio was ~8:1, slightly higher than the minimal value of 5:1 recommended in the literature. AMOS (v.19) was the software platform used to test the proposed path model.

#### Results from Basic Statistics

Table 2 presents the basic statistics for each of these measured continuous variables at the exit point and includes both the endogenous (dependent) and exogenous (independent) variables. The correlation analysis results confirm the two predictions made in the proposed path model. First, perceived engagement shows a statistically significant positive correlation to course self-efficacy while perceived difficulty shows a statistically significant negative correlation to both self-efficacy and final grade. This finding suggests that course self-efficacy is a potential partial mediator between perceived difficulty and final grade. Second, self-efficacy shows a statistically significant positive correlation to the final grade.

Table 2. Path Model Analysis: Basic Statistics for Path Variables.

Variable	Basic Statistics						
	Exit	1	2	3	4	M	SD
1. Perceived engagement [1-9]	-	-.13	.36*	.17	7.07	1.21	
2. Perceived difficulty [1-9]		-	-.43**	-.54**	6.32	1.85	
3. Course self-efficacy [1-5]			-	.55**	4.33	.62	
4. Final grade [%]				-	81.16	9.21	

Notes: \*  $p < .05$  (2-tailed); \*\*  $p < .01$  (2-tailed)

### Overall Model Fit and Results

Figure 2 summarizes the resulted path coefficients and their statistical significance. The proposed predictors shown in the path analysis model were measured in the exit survey using the validated scales discussed in the procedure and instruments section.

The minimum discrepancy measured by chi-square was not significant ( $\chi^2(3) = .26, p = .97$ ) which indicates that there is an adequate close fit between the hypothesized model and the perfect fit model [6, 16]. The adequacy of fit is also strengthened by the value of the ratio of the minimum discrepancy to the degrees of freedom,  $CDMIN/DF = .09$ , which is significantly smaller than 2.0 as recommended in the literature [6]. All major goodness-of-fit statistics recommended in the literature [6, 16] indicated a good fit for the proposed models, as follows:

- a) Goodness-of-fit index,  $GFI = .99$ , and adjusted-goodness-of-fit,  $AGFI = .98$ , both higher than .95, the recommended critical value;
- b) Comparative fit index,  $CFI = .99$ , higher than .95, the recommended value, and

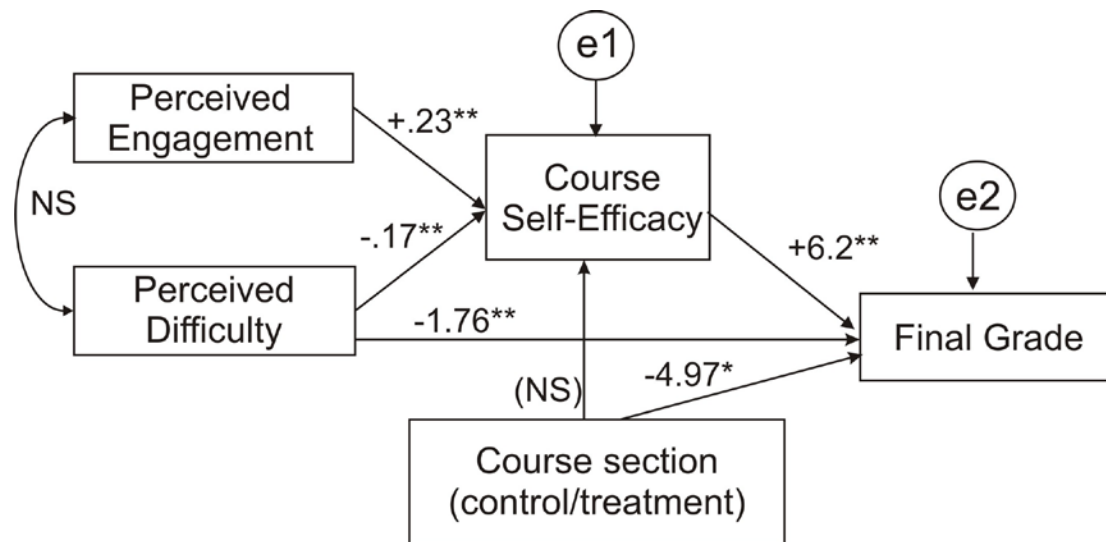
- c) Root mean square error of approximation,  $RMSEA = .001$ , smaller than .06, the value recommended by the literature [16].

In addition, critical sample size statistic, Holter ( $p = .05$ ) = 1320 was much higher than 200, a value that is indicative of a model that adequately represents the sample data used [6].

The analysis of path coefficients indicated *several expected findings*. First, perceived engagement was a significant positive predictor of self-efficacy, and self-efficacy was a significant positive predictor for the final grade. Second, perceived difficulty was a significant negative predictor for the final grade, and this impact was partially mediated by self-efficacy. Finally, as for unexpected findings, the enrollment section (1-traditional or 2-blended lecture) had a statistically significant negative impact on the final grade.

However, a one-way ANOVA analysis indicated no statistically significant difference in final course performance (final percentage score) between the traditional lecture group ( $M_{\text{traditional}} = 82.2$  [%]) and blended instruction with online lecture group ( $M_{\text{online}} = 78.0$  [%]).





Note: Significance of Standardized Path Coefficients \*  $p < .05$ ; \*\*  $p < .01$ ;

Figure 2. Path Coefficients for the proposed model.

Therefore, even if the group engaged in the blended instruction with online lecture had a smaller mean final percentage score in the course, *from a statistic validation perspective the group of students in the blended-format with online lectures performed similarly to the control group in the face-to-face lectures*. That is, at least for this pilot implementation of this blended instruction strategy, *the “virtual professor” and the “live” professor performed at a comparable level*. Some possible causes for this apparent contradiction between the results of the proposed model and the direct comparison of the performance of the treatment and control groups will be discussed in the conclusion section below.

### Conclusions and Further Research

First, the proposed model tested in this study confirmed previous findings from studies in the literature: a) self-efficacy is a significant predictor for students’ final performance [14, 17] and b) perceived motivation and perceived difficulty are significant predecessors of self-efficacy [10, 18]. Therefore, *self-efficacy can be considered as a candidate measure for monitoring students’ learning progress throughout the semester*.

That is, future research will be needed to validate in a full implementation of this strategy the proposed model at various major points in the instructional process, such as major semester exams.

Further research might also be needed to *identifying a threshold value for self-efficacy and its major determinants* that signals potential failure and help instructors focus their attention on at-risk students at a point where failure can still be avoided.

Second, the results of this study indicated a discrepancy between the results of an ANOVA analysis of final performance and the negative path associated with the type of lecture in the proposed model. That is, while ANOVA showed no statistically significant differences between the final performance means of the two groups, the negative path between the group type (treatment and control) and final performance was statistically significant.

One potential cause for this discrepancy might reside in the increased sensitivity of the overall path analysis model proposed when compared with the sensitivity of the final scores alone. Another potential cause might be the relatively

low sample size used in this study which is detrimental to direct group comparisons as is the case of the analysis of variance.

However, the negative path above mentioned suggests the potential of harm for the students' performance when they are exposed to online lecture modules in a mainly face-to-face instructional environment where the strong self-management skills required by the online learning are not emphasized. This concern is in line with previous research findings conducted at the same university where this study was conducted [21]. This potential harm is also supported by more generic findings in the literature that show a far smaller retention rate for online students when compared to face-to-face alternative [22]. More research is therefore needed for identifying future instructional interventions that can increase students' motivation, reduce the perceived difficulty associated with online learning and therefore maximize self-efficacy with the goal of improving final performance outcomes.

Possible future research direction might include analyzing: a) the validity of the proposed model for a larger number of participants when the online modules will be fully implemented in the course, b) the impact of additional formative feedback for students who are using online lecture modules or c) the impact of online student orientation strategies on students' motivation and perceived difficulty [7].

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### Biographical Information

Dan Cernusca is currently an Assistant Professor of Practice/ Instructional Design in the School of Pharmacy, Nursing and Allied Sciences at the North Dakota State University. Previously he was an Instructional Design Specialist with Missouri University of Science and Technology. He received his Ph.D. in Information Science and Learning Technologies in 2007 from the University of Missouri, Columbia. His research interests include Design-Based Research in technology-rich learning environments, technology-mediated problem solving, application of dynamic modeling for learning of complex topics and impact of students' beliefs on learning with technology.

Clayton E. Price is an Associate Teaching Professor in the Computer Science department at the Missouri University of Science and Technology (S&T). He has varied interests in the sciences, having earned degrees in geology/geophysics, mathematics, and computer science. He has taught at S&T for 33 years, and currently he teaches courses in introductory programming classes in C++ and numerical analysis. His interests center on his teaching and investigating new paradigms for instructing students in higher education settings.

## Appendix

### *Course Self-Efficacy*

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Please indicate how much do you agree or disagree with the following statements.  
(1 strongly disagree to 5 strongly agree)

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1 I'm certain I mastered the skills taught in this course

2 I'm certain I was able to figure out how to do the most difficult course work

3 I was able to do all the work in this course when I didn't give up

4 Even if the work was hard, I was able to learn it

5 I did even the hardest work in this course when I tried

6 I am certain I understood the ideas taught in this course.

7 I was able to learn the material for this class.

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Notes:

Items 1 to 5: Academic Efficacy scale [12, 13];

Items 6 and 7: Self-Efficacy scale [15]