Promoting Success In Online College Courses: Understanding Interactions Between Course Structure And Learner Readiness

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Abstract

Why do some students do well in online courses while other equally capable students do not do well? Are there students who are more likely to complete an online course than a classroom course? This study found that student retention and success appear to be related to an interaction between a student's readiness to learn a particular subject and the structure of the course. In this study, readiness to learn was characterized by a student's motivation, learning practices, preference to work alone or with others, and affinity for using technology for learning, while a course is characterized by its level of teacher and student centeredness, and the course delivery mode. By developing a better understanding of this interaction and its impact on learning we can try to design both online and classroom courses to meet the needs of a more diverse student population.

Traditional approaches to comparing the outcomes of classroom and online students yield the same finding again and again: There is no significant difference in the performance of classroom and online students (Russell, 1999). In fact, some wonder why one would conduct new research in this area at all. My concerns with much of the research are: 1) Most studies only compare the outcomes of course completers, without examining the high attrition rate in many online courses, 2) classroom "lecture-led" courses are compared with online courses with no lectures, overlooking the effects of the lecture environment itself, and 3) initial student differences relative to characteristics of the distance learning mode (i.e. the isolated learning environment and a less familiar structure than attending lectures) are not investigated or controlled. Ultimately, we don't learn much about what teachers might do to design online courses that encourage retention as well as academic success from such studies.

My experience teaching undergraduate online courses led me to wonder why some students did well in online courses while other students of the same age and with the same academic background did not do as well; in fact I observed many capable students withdrawing from online courses. The study presented here was an attempt to determine what, if anything, might be done to encourage more students to persevere and complete online courses successfully.

The study design represented an improvement over many prior studies because it investigated course completion as well as the performance of completers, it compared classroom and online courses that were structurally similar (i.e. both required students to take initiative in engaging in learning activities rather than listen to lectures), and it controlled for initial student qualities such as self-reliance and study habits. The study sought to disentangle a number of interrelated factors affecting college student performance in online courses: student characteristics, course structure, and course delivery mode.

Online courses may differ from classroom courses in a number of ways including the proximity of the students to the teacher and to one another, the synchronicity of participating in the course, the manner in which course content is delivered, and the ways students interact with the course material, the teacher, and other students. This study attempted to isolate the influences on student outcomes stemming from pedagogic, or course structure, components from those stemming from delivery components. In addition, students in the study were characterized in relationship to the courses they were enrolled in; their *readiness to learn* was situated in the context of a specific course. The findings from this study may help clarify the reasons students who have been successful in classroom courses may not be as successful in online courses and why capable students may not complete online courses as readily as classroom courses. This information may then help identify areas in which online courses can be changed to improve student retention and performance.

This paper is organized to 1) define the learner readiness variables that were used to control for initial student differences, 2) describe the learner-centered pedagogy that was used in both the online course and the classroom course, 3) describe the quasi-experimental design of the study, 4) present the behaviors found to be associated with retention and learning for different types of students, and 5) discuss some implications of the findings.

Theoretical Framework

Learner Readiness

Standard approaches to evaluating the effects of teaching strategies on student outcomes tend to rely on the use of straightforward demographic information to control for initial differences in students. Many studies control for age or years of schooling as a proxy for "academic preparation." This approach fails to recognize the differences one may find in students of the same age or same year in school. In addition, it fails to consider motivational aspects that may influence the effort a student will expend in learning. A new approach to measuring student characteristics that influence a student's *readiness to learn* in a given context was developed for this study. Four variables emerged to measure this readiness: perception of course relevance, responsibility for learning, preference for interaction, and affinity for using technology.

In Spring 1999, the first pilot study was conducted to develop a questionnaire that would measure a student's level of engagement in classroom and online courses (Kennedy, 1999, May). That study of 286 community college students led to a refinement of the instrument with a more extensive set of items measuring multiple dimensions of engagement. The second pilot study was conducted in Fall 1999 among 305 students from the same college (Kennedy, 2000, March). That study helped to define five aspects, or dimensions, of engagement in college courses that were appropriate when some, or all, of the course activity required the use of computers. These dimensions were: the purpose for taking the course, the level of interaction with the teacher, typical study activities, attitude about using computers, and experience using computers. Further review of the literature about distance learning suggested a slight change of focus from *engagement*, which was intended to measure a condition during participation in a course, to *readiness to learn*, which was intended to measure student perceptions and characteristics before experiencing a course. Readiness to learn was hypothesized as situated because it could be different in different courses. For example, we might expect higher readiness for students enrolled in courses in their majors than for those enrolled in General Education courses; or students who have decided on a major may have higher readiness in general than students who have not yet decided on an educational goal. The third pilot study of the instrument, conducted in Spring 2000 among 221 students enrolled in classroom and online courses, resulted in a final instrument of 50 items that measured four dimensions of readiness: Perception of Course Relevance, Responsibility for Learning, Preference for Interaction, and Affinity for Using Technology (Kennedy, 2000, August). These dimensions, or variables, are considered latent because they cannot be observed directly. In developing the variables, each met the following requirements for measurement defined by Wright and Masters (1982):

1) The reduction of experience to a one dimension abstraction;
2) *more* or *less* comparisons among persons and items;
3) the idea of linear magnitude inherent in positioning objects along a line; and,
4) a unit determined by a process which can be repeated without modification over the range of the variable (p. 3).

The multidimensional random coefficients multinomial logic (MRCML) model (Adams, Wilson & Wang, 1997) was used for the item response theory (IRT) analysis because it is a generalized model that can be applied to a number of special cases. The ConQuest computer program (Wu, Adams & Wilson, 1998) was used for the computations. The MRCML model uses marginal maximum likelihood (MML) estimators to determine item difficulties and person abilities across one or more latent variables. MML is used for estimating parameters by assuming that persons have ability estimate vectors sampled from a population in which the distribution of abilities comes from a multivariate density function $G(\theta; \alpha)$, where α is a vector of parameters that characterize the distribution $G(\theta; \alpha)$ (for example, a mean and standard deviation for a univariate model).

The MRCML assumes a set of D latent variables, with person-positions in the D-dimensional latent space represented by the vector $\theta = (\theta_1, \theta_2, \ldots, \theta_D)$. The scoring function b_{ikd} represents a response in category *k* on item *i* in dimension *d*. The scoring matrix, B, is comprised of vector elements for a given item and response category across the range of dimensions. The item parameter vector, ξ, is usually comprised of item and step difficulties, and the design matrix, A, is comprised of one or more rows for each item, with a column for each item parameter. The probability of a response in category *k* on item *i* is then

$$P(\mathbf{x}_{ik} = 1; A, B, \xi \mid \theta) = \frac{e^{(\mathbf{b}_{ik}\theta + \mathbf{a}'_{ik}\xi)}}{\Sigma e^{(\mathbf{b}_{ik}\theta + \mathbf{a}_{ik}\xi)}} \tag{1}$$

and the response vector is

$$f(x; \xi|\theta) = \Psi(\theta, \xi) \exp[x'(B\theta + A\xi)], \text{ where } \Psi(\theta, \xi) = \{\Sigma \exp[z'(B\theta + A\xi)]\}^{-1} \tag{2}$$

The multivariate density function, G(θ; α), is applied to obtain the marginal density of the response pattern x_j for person *j*. The likelihood equations of the item and population parameters are derived as cumulative products of the relevant response vectors.

The outcome of these analyses provided a reasonable calibration of 50 Likert-type items to describe person positions along a continuum for each variable. The Spring 2000 pilot data was combined with the Fall 2000 data gathered for this study and data for a larger study of 15 additional sections of online and classroom students, conducted during the same semester for a total of over 700 cases to generate the item calibrations used here. To determine whether each selected set of items defined a variable sufficiently, construct validity was evaluated, essentially testing that the pattern of item calibrations made sense. Figures 1 through 4 show the items for each variable, ordered by the difficulty of endorsing the statement. The statement at the top of each continuum was the most difficult for students to agree with while the statement at the bottom was the easiest to agree with. None of the items from the final questionnaire appeared to be out of place in the context of each variable.

--- Figures 1 through 4 about here ---

Item fit statistics were examined and no item had a weighted mean square value smaller than .75 or larger than 1.33 (this is a commonly accepted range around the ideal value of 1.00). Having all item weighted mean square values sufficiently close to 1.0 indicates that the items are working together to define a single quality. In other words, the items appeared to "fit" the overall learner readiness model we wanted to measure.

Person separation indices were also analyzed to examine the extent to which individuals were differentiated by the model. The person separation indices, which ranged from .635 to .770, suggest moderately good variance in the person estimates to differentiate persons sufficiently well for the analyses in the study. Figures 5 though 8 show the population distributions for each variable.

--- Figures 5-8 about here ---

The Perception of Course Relevance Variable

Course relevance is related to a student's perception of the importance of the course content. Development of this variable was guided by the literature on the motivation of college students, adult learning, and distance learning (Candy, 1995; Knowles, Holton & Swanson, 1998; Moore & Kearsley, 1996; Pascarella & Terenzini, 1991).

When we think about the motivation behind students choosing to enroll in a course, it is important to consider not only their interest in the subject, but why they enrolled in a course rather than learn the material in some other way, or why they enrolled in a specific section of the course rather than another section. Thus, a student's perception of course relevance evaluated how important enrolling in the particular section of a course was to the student. The Perception of Course Relevance variable was assessed through a series of 13 Likert-type items in response to the prompt, "How important were the following factors in deciding to take this course?" with choices of "Extremely Important," "Very Important," "Somewhat Important," and "Not Important" in response to statements such as, "I wanted to get teacher guidance and feedback in this subject." The items are listed in Appendix A.

Most students enrolled in courses they had some interest in, that met degree or certification requirements, and were offered at a convenient times. Note that these characteristics are representative of endorsements of items at the bottom of the continuum in Figure 1. Students with somewhat stronger reasons for taking the course indicated that they also wanted the support of the teacher and the structure of a course, indicating endorsements of items around the middle of the continuum in Figure 1. We might infer that these students either wanted to get the most out of the course or knew that they needed some external support to learn or to stay motivated. Students who reported the greatest need for taking the course were those who either had an immediate need of the course content (i.e. for a job), or who sought interaction with other like-minded students and the expertise of a particular instructor (in either the subject area, in teaching reputation, or in both). These students were most likely to also endorse items shown at the top of the continuum in Figure 1.

Thus, the Perception of Course Relevance scale can be thought of as a continuum from interest or curiosity in the subject, to wanting support in the pursuit of learning, to a more intentional seeking out of a community of learners with a common interest.

The Responsibility for Learning Variable

This variable measures a student's commitment to learning and initiative in engaging in learning activities. Development of this variable was guided by the literature on attribution theory and metacognition (Brown, Bransford, Ferrara & and Campione, 1983; Clayton-Jones, L., Rodwell, K., Skehan, J., Archer, J., Chan, L. & Moore, P., 1992; Cross, 1996; Gibson, 1996).

The Responsibility for Learning variable was assessed through a series of 10 Likert-type items in response to two different prompts. The first prompt, which assessed students' attribution beliefs, was, "How have the following factors contributed to your success in previous courses?" and had response choices of "Extremely Important," "Very Important," "Somewhat Important," and "Not Important" to statements such as "The teacher's lectures." The second prompt, which assessed the effort students made in studying, asked, "What are your usual study habits?" and had response choices of "Always," "Often," "Seldom," and "Never" to statements such as, "I do my homework regularly." The items are listed in Appendix A.

The most responsible learners were those who made the most effort in accessing information about a subject and enjoyed the endeavor. Those who were somewhat less engaged were still curious about how well they had answered difficult test questions and valued the process of doing homework and the feedback and guidance their teachers provided. These students were also likely to say that they were sufficiently self-motivated to study on a regular basis. Students who took the least responsibility for their learning outcomes were less inclined to monitor their learning activities and tended to do the minimum required by the instructor. Although they did attribute their academic success to their own effort and study habits, they may not have known what else they could do to perform well in a course, or they may have been satisfied with the progress they were making. As shown in Figure 2, this continuum reflects a level of engagement in learning activities, from completing assignments, to monitoring progress and taking corrective action, to going beyond what is expected.

The Preference for Interaction Variable

The Preference for Interaction variable measures student positions along a continuum from "prefers to work alone" to "prefers to work with others." Development of this variable was guided by the literature on social aspects of college, social cognition, and learning communities (Brown & Campione, 1996; Gabelnick, MacGregor, Matthews, & Smith, 1990; Pascarella & Terenzini, 1991; Vygotsky, 1978).

The variable was assessed through a series of 13 Likert-type items in response to the two prompts described previously for the Responsibility for Learning variable and a third prompt, "How do you usually interact with your teachers?" This prompt had response choices of "Always," "Often," "Seldom," and "Never" to statements such as, "I ask questions in class." All of the items are shown in Appendix A.

Students with the least preference for interaction, that is, those who were the most reserved, made the least effort to meet with other students or their teachers outside of class, although they valued the availability of their teachers during office hours or by email, and felt that they benefited from working with other students during class time. Students with a stronger preference for interaction were more likely to respond to questions asked in class and believed that they learned from other students, as well as from the teacher, but they were still not likely to meet with other students and their teachers outside of class time. The most outgoing students contacted one another by phone or email, may have organized study groups, and were more inclined to talk to their teachers outside of class time, even about subjects beyond the scope of the course. These qualitative levels correspond to endorsement of the items shown in Figure 3.

The Affinity for Using Technology Variable

This variable is of particular importance when we consider the relationship of student performance to the delivery mode when it includes technological components. A student's affinity for using technology measures whether the student enjoys and values using computers to do his or her work, or considers the computer an obstacle to be overcome in order to participate in a course. Development of this variable was guided by the literature on computer-mediated and computer-assisted interaction and their impact on students in online learning environments (Almeda, 1999; Hara & Kling, 1999; Jones, 1998; Keating & Hargitai, 1999).

Affinity for Using Technology was assessed through a series of 14 Likert-type items in response to two prompts. The first prompt, "How do you use computers?" had response choices of "Daily," "Weekly," "Seldom," or "Never" to statements such as, "I check my email." The second prompt, "How do you feel about the following uses of computers?" had response choices of "Strongly Agree," "Agree," "Disagree," "Strongly Disagree," or "Never Tried" to statements such as, "I enjoy participating in online chats or conferences with other students from my classes." The items are shown in Appendix A.

As shown in Figure 4, students with the least affinity for using technology did use email, accessed the Internet for school or work, and used word processors. They also felt that online courses were a good alternative for students who could not take college courses on campus. Those with a moderate affinity for using technology accessed the Internet more often and for more varied reasons, and were more sophisticated computer users in that they were more likely to know how to use spreadsheets or databases. They also felt that college students could learn as much online as in the classroom. Students with the most affinity for using technology engaged in more sophisticated Internet activities such as conferencing and chatting online, and were more likely to play Internet games or communicate online with people they didn't know. The affinity for using technology continuum was largely a gauge of how involved the student was with the Internet community. Those who are part of the community were comfortable conversing online with individuals they had never met, while newcomers were more likely to use the Internet as an alternative to familiar activities, such as using email instead of the telephone, and accessing the Internet instead of visiting the library.

The Adaptive Instructional Strategy (A.I.S.)

A primary goal in this study was careful control of the way students participated in online and classroom sections of the same course. A common difference between the experiences of classroom and online students is the way course material is acquired. In many undergraduate classrooms, teachers research the subject to be presented and then filter, synthesize, and distribute “relevant” material to students during lectures comprising about two to three hours of class time per week. In online courses the burden is often on the student to read vast amounts of material and determine the “relevant” parts for themselves. One objective of the A.I.S. pedagogy developed for this study was to make learners in the online and classroom courses equally responsible for actively engaging in learning activities. A.I.S. classroom students did not receive 3-hour lectures from which all of the test questions could be anticipated. In addition, the pedagogy was designed to provide sufficient structure to be supportive of less experienced or capable students while providing enough flexibility to meet the diverse needs of today's busy collegiate population, whether in physical or virtual classrooms. The A.I.S. courses in the study (classroom and online) provided ample opportunities for student-student and student-teacher communication and feedback, while attendance and some assignments were optional.

The pedagogy was grounded in the concept of learner-centered teaching (e.g. Knowle's, 1998; Rogers, 1969), Moore's (1996) theory of transactional distance, and Vygotsky's (1978) theory of social constructivism. Knowle's approach to learner-centered teaching emphasizes three domains of adult learning: The goals and purposes for learning, individual and situational differences, and adult learning principles. The learner is viewed as an integral contributor in determining appropriate learning processes to be employed in a course. Transactional distance theory asserts that achievement is strongly associated with an interaction between learner autonomy and course structure. Less autonomous learners need more teacher direction and formal structure than highly autonomous learners. Social constructivism emphasizes the importance of the learner actively seeking understanding as a strategy to improve learning; it can be contrasted with a teacher-centered approach that emphasizes teachers disseminating most of the course content through lectures.

Four key linkages between theory and practice guided development of the Adaptive Instructional Strategy:

1) Learning involves both cognitive and social elements, making the conditions of learning as important as the instructional content.
2) Learner-centered teaching accommodates individual goals and purposes for learning and considers the learner an integral contributor in determining appropriate learning processes.
3) Learner autonomy must balance with the transactional distance of the course.
4) Assessment of student achievement should reflect learning theory.

The A.I.S. pedagogy, which is modeled in Figure 9, was designed to enhance students' readiness to learn by increasing their perception of course relevance and fostering their responsibility for learning. At the same time, the pedagogy accommodated individual students' preferences for more or less interaction with their peers and instructor, as well as their affinity for using technology. A primary aspect of the pedagogy was the flexibility it offered, such as communication alternatives and grading options, to enhance learner control of the course structure.

--- Figure 9 about here ---

Methodology

Quasi-Experimental Design

The population for the study was 164 students enrolled in three sections of the same course taught by the same instructor (who was the author) at College of San Mateo, a community college, in the Fall 2000 semester. One section was taught in the classroom in the traditional lecture-based mode, one in the classroom using the A.I.S. pedagogy and one online using the A.I.S. pedagogy. Since this study focused on exploring the reasons students select online and classroom courses, as well as performance outcomes, an experimental design with random assignment was not appropriate. Instead a non-equivalent groups design was utilized and, as was mentioned in earlier sections, a concerted attempt was made to make the experience of students in the classroom and online A.I.S. groups as similar as possible. Initial student differences were also controlled in the analyses.

Data used to answer the questions under investigation were gathered through administration of student questionnaires at the beginning and end of the semester, pre-tests of content knowledge administered at the beginning of the courses, interviews of students conducted at the middle and end of the semester, teacher logs of how students interacted during class time, computer logs of student participation in online chats and conferences, telephone exit interviews of students at the time they finished or dropped a course, and post-tests of content knowledge.

The course taught was an introductory course in computer networks, usually the first or second course a student takes in a series of courses to become a network engineer or computer programmer. At the beginning of the semester, the teacher explained to each class that the course assumed the audience was comprised of three groups: people who intended becoming network engineers, people who intended becoming programmers who would develop applications to be deployed over the Internet, and people who wanted to learn more about building networks and connecting to the Internet from home. One purpose of this explanation was to immediately help students develop a sense of the relevance of the course to their professional and personal goals.

The traditional classroom section was taught in the evening and met once a week for three hours. Class time was spent primarily in lecture, with teacher-posed questions to initiate discussion during the last 30 or 45 minutes of class time. The questions were related to applying the concepts to case studies the students were working on, and were intended to familiarize students to the role they would play as networking experts in real world situations. Typical questions included: What would you ask the client about the symptoms he or she was experiencing?; What clues would you look for in the hardware?; and, If you were communicating over the telephone, what would you ask the client to do and report back to you? Students were also encouraged to ask questions periodically during the lecture. When students had no questions to ask, the instructor would pose questions to the students to reveal general misunderstandings about the concepts presented. Students were graded for participation based on course attendance.

The A.I.S. classroom section was taught in the evening and met once a week for three hours. Half of the class time was spent in small group discussion working on the currently assigned case study or another practical application of the topic for that week. Students were encouraged to form groups of three or four to discuss the problem and present their findings, but students were permitted to work alone and present their solutions individually if they preferred. Students were provided a handout of the problem and a series of steps to follow to arrive at a solution. Most problems had a number of possible solutions. The instructor went from group to group to ask if students needed clarification on any parts of the problem, or to ask about how students were progressing in finding a solution. In some cases, the instructor offered hints about how to approach the problem. Solutions were discussed informally, rather than presented from the front of class, with the purpose of providing students an opportunity to observe how other students had approached solving the problem. The other half of the class time was spent in a spontaneous lecture by the instructor that focused on student misunderstandings that became apparent through the group activity and ensuing discussion of possible solutions and formal questions students were asked to bring to each class meeting. As an incentive to get students to read the material before class they were given credit for submitting discussion questions before class started. Students were given a participation grade based on the number of times they submitted these written questions which were used as a basis for the mini-lectures.

The online section was presented as a series of lessons with study questions for each week; these study questions paralleled the topics discussed in the lectures of the traditional classroom course. Students were required to participate online each week, either by submitting a question to the class discussion board for the current topic, answering a question on the discussion board, or asking a question of the instructor through personal email. This was the basis for online students' participation grade.

From the third week on, students in each section completed a performance activity every week: a quiz, a case study, or a test. Four quizzes were administered, five case studies, and two tests (a midterm and a final). Each quiz was comprised of 20 multiple choice questions related to the textbook reading. Case studies required students to analyze and evaluate alternative solutions to troubleshooting problems they were likely to encounter in the real world, thereby applying the concepts they had studied most recently. The midterm and final exams were each comprised of 25 multiple choice questions related to the textbook readings and five open-ended questions related to the case studies, each worth 5 points. All students took the same quizzes and tests and completed the same case studies, with each student submitting his or her own case write-up (i.e. no group grades).

Findings About the Research Design

Two questions relate to the study design itself. First, what do we gain by separating the effects due to the course structure (i.e. teacher-guided vs. student-guided) from the effects due to the delivery mode (i.e. classroom vs. online). And second, what do we gain by using the learner readiness variables.

Separating the Effects of Course Structure and Delivery Mode

Traditional Analysis – Testing the Online Condition Only

Initial regression analyses indicated that the only demographic factor associated with course completion was whether the course students were taking was their first in the subject. Students were more likely to complete the course when it was their first exposure to the subject. When we control for first exposure, a traditional analysis of the online treatment shows that it has a negative association with course completion (at the α=.01 level).

Age and pretest performance did appear to be statistically significant predictors (at the α=.01 level) of test performance when GPA and the online format were controlled, and age, GPA and pretest performance were all statistically significant predictors of course grade when the online format was controlled (age and GPA at the α=.01 level, pretest performance at the α=.05 level). When age, self-reported GPA, and pretest scores were controlled in analyses of test performance and course grades, the online format had little association with test performance or grade attainment (p=.800 for test performance and p=.302 for course grade). Hence, it appeared the "no significant difference" phenomenon for academic outcomes would be supported by this study.

New Analysis – Separating the Structure and Delivery Mode Conditions

When we separate the conditions of course structure and delivery mode, we do learn a bit more about the effect of being in one class rather than another as that choice relates to test performance and course grade attainment. It appears that being in a student-centered course is associated with lower test scores and lower course grades than being in a traditional, teacher-centered course. As shown in Table 1, students in the traditional classroom course earned about 5 percent more on their course grades and on their test scores than students in the A.I.S. courses (p=.015 and p=.013 respectively). When age, prior GPA, pretest score and the delivery mode were controlled the associations became somewhat weaker (4 percentage points difference with p=.054 for course grades and p=.066 for test scores). The t-tests comparing the outcome differences for A.I.S. classroom and online students showed no evidence of significant differences in course grades or test scores. Thus, we have some evidence suggesting that academic performance in an online course may be due to the course structure rather than to the delivery mode.

--- Table 1 about here ---

However, when we test both conditions in the analysis of course completion, the model with the additional course structure condition is not an improvement over the original model. So it appears that course structure is not significantly associated with retention. Comparison of the two models for each outcome variable are shown in Table 2.

--- Table 2 about here ---

Adding the Learner Readiness Variables to the Analyses

Learner readiness characteristics were evaluated twice for each student. At the beginning of the semester, the questionnaire asked about what students anticipated about the course (i.e. course relevance) and what their past practices had been in prior courses (i.e. preference for interaction, responsibility toward learning, affinity toward using technology). Thus, there were effectively three learner readiness measures: initial student characteristics, what students reported doing in the current course, and the extent to which what they did in the courses under study was different from past practices.

Although students in the three groups were statistically similar (significance tests ranged from .221 to .910 for each of the variables) in age, self-reported grade point average, gender, units completed, employment status, whether the course was the first they were taking in the subject, and pretest scores, students in the three sections differed in their initial learner readiness characteristics (see Table 3 for more detail):

- Students in the two classroom sections had significantly higher initial perceptions of course relevance than students in the online section ($p=.004$ comparing all classroom students with online students).
- Students in the A.I.S. classroom section had significantly higher initial preferences for working with others and reported higher initial levels of responsibility toward learning than students in the traditional classroom section or the online section ($p=.002$ for interaction and $p=.018$ for responsibility comparing classroom A.I.S. students with traditional classroom and online students).

- Students in the online section had significantly higher initial affinity for using technology than students in the classroom sections ($p=.032$ comparing all classroom students with online students).

--- Table 3 about here ---

Initial learner readiness characteristics were not strongly associated with test scores or course grades, although a high affinity for using technology was associated with students not completing their courses (std. coeff. = -.212, $p=.004$). However, when learner readiness characteristics were controlled, the delivery mode and course structure were no longer statistically significant predictors of academic performance or course completion, suggesting that there may be interaction effects between course structure and student characteristics.

Predictive Power of Learner Readiness Characteristics

The analyses of academic outcomes that follow controlled for student age, prior GPA, pretest score, course structure and delivery mode and include only course completers. The analyses of course completion controlled for first course in the subject, course structure, and delivery mode and included all students who started the course.

Learner readiness characteristics measured at the end of the term did provide insights about the circumstances associated with student success. Students who interacted more with others earned higher test scores than students who interacted less (std. coeff. = .324, $p=.013$) and students who exerted more effort in the course earned higher course grades than students who made less of an effort (std. coeff. = .279, $p=.044$). Contrary to the positive association of exerting more effort in the course with earning a high grade, students who exerted more effort were also the most likely to withdraw from their course (std. coeff. = -.248, $p=.021$). Apparently, students were more likely to complete the course when they didn't have to work so hard.

To further understand these findings, a third analysis was performed, comparing the learner readiness characteristics at the end of the term with those at the start. In this analysis we found that exerting more effort in this course than in past courses was associated with earning higher grades (std. coeff. = .249, p=.021) but with a greater likelihood of withdrawing from the course (std. coeff. = -.413, p<.001).

Findings from the Comparison of Classroom and Online A.I.S. Students

One limitation in the preceding analyses was that there was no combination of conditions to account for "traditional" course structure and the "online" delivery mode. A final set of analyses looked for interaction effects between delivery mode and student characteristics to help explain student outcomes. In this set of analyses, the online and classroom courses were as similar as possible, with both using the A.I.S. pedagogy.

Initial Differences

The distribution of students in the online and A.I.S. classroom sections was generally similar, although the online section had a higher percentage of students who were more experienced college students (49% of classroom students v. 57% of online students had completed more than 60 college units; see Table 4). Students in the two groups also performed at similar levels on the pretest, but the students were quite different in their readiness to take the course (see Table 5).

--- Tables 4 and 5 about here ---

On average, students in the online section were more reserved and self-reliant, were less engaged in learning activities, and expected the course to be less relevant than students in the classroom section. They also tended to have a higher affinity for using technology than classroom students, although this difference was not as great as the other differences.

The results from a binary logistic model predicting the online course selection from the student readiness characteristics while controlling for age, grade point average and pretest score are shown in Table 6. The relatively large parameter estimates (column B), significant at the α = .05 level, for affinity for using technology (B = 1.1058, p = .0153) and preference for interaction (B = -.7172, p = .0296) confirm that even when other variables are controlled, these two characteristics were strongly associated with students' decisions to enroll in the online or classroom section of the course. A one unit increase in affinity for using technology (std. dev. = .7407, 1 unit = 1.35 std. dev.) tripled the odds of enrolling in the online section rather than the classroom section ($e^{1.1058}$ = 3.022), while a one unit increase in preference for interaction (std. dev. = 1.2391, 1 unit = .81 std. dev.) doubled the odds of enrolling in the classroom section rather than the online section ($e^{.7172}$ = 2.049).

--- Table 6 about here ---

Students who chose to enroll in the online section clearly preferred less interaction with others. This means they were less inclined to speak up in class, to meet with their teachers, or to initiate dialogs with other students inside or outside of class time. In addition, these students tended to attribute learning to their own effort rather than to the contributions of others. One can interpret from this that students were thoughtful about deciding to enroll in an online course and understood that taking a class online is a very independent way to learn. It was not surprising to find that students in the online section had a higher affinity for using technology than students in the classroom section, since the affinity measure includes a positive attitude about using online technologies for learning. This correlation also conforms to the finding that students who reported having a low affinity for using computers tended to select the classroom course delivery mode.

A surprising finding was that students who expected the course to be the least relevant to them chose the online section rather than the classroom section. Although this indicator is not as strong in the multivariate analysis as in the univariate analysis (i.e. Table 6 v. Table 5, respectively), it appears that students who expected the course to be highly relevant to them selected the classroom section rather than the online section (odds ratio = $e^{.5604}$ = 1.751). This suggests that students enroll in a classroom course, where they have an opportunity to interact with the professor and other students who are interested in the subject, when they most need to learn the course content. As one student put it, "If I really had the time to go school, I would definitely do that, because listening to the teacher's lectures is more helpful than studying all by yourself." Perhaps online courses are seen as a convenience that is most appropriately utilized for taking classes that are not perceived as critical to the student. When students have a great interest in the subject, or believe they need to learn it well, they appear to value the time they have with an expert and so enroll in a classroom course.

Findings

Course Completion

Students were considered course completers if they completed the final exam. Several analyses controlling for differing factors yielded the same finding: Classroom students were more than twice as likely as online students to complete their course. Novice students (i.e. those taking their first course in the subject) were more likely to complete both the classroom and online courses, and an affinity for using technology was negatively associated with completing for both groups. This latter finding may suggest that those already familiar with technology did not feel as great a need for completing the course (which was about computer technology) as those who were less familiar with technology to begin with. As one can determine from Table 7, even when we control for these two factors, classroom students were more than twice as likely as online students to complete their course ($e^{.8124} = 2.25$).

--- Table 7 about here ---

As shown in Table 8, online students with a low preference for interacting with others (i.e. those who were more self-reliant) were more likely to complete their course than online students who preferred more interaction, but this did not appear to be an important predictor for classroom students. Typical comments from students who withdrew from the online course because they wanted more a more personal connection included:

> "I decided to withdraw because I need interaction with the teacher and students, and find it very difficult to take a class over the Internet. You don't get the same 'teaching' when you're not in a class."
>
> "I thought I would love the online classes since I have a daughter at home and I like computers, but I have found that I miss the immediacy of classes. It's nice to have someone there to answer questions. I like the flexibility of working on my own schedule, but my first choice will remain classes on campus."

--- Table 8 about here ---

And, although online students tended to have lower perceived need of the course than classroom students, this factor was not strongly associated with whether or not they finished the course. In fact, adding more covariates (i.e. level of employment, prior GPA, etc.) to the model did improve the reliability of the model, but no new significant predictors of course completion emerged. Responses to open ended questions asking why students withdrew from the course did suggest that employment was a factor, although the quantitative analyses did not bear this out. This may be because it is the nature of one's job that matters, rather than the part-time or full-time status, which was captured in the instrument. In addition, some student's job requirements changed after the course started, and this situation was not captured by the initial questionnaire either. Representative comments from students who withdrew because of job obligations follow.

> "My working hours increased from 12 to 30 hours per week. I did not have the time to dedicate to this class."
>
> "I withdrew because of a conflict with my work schedule."
>
> "Current job didn't allow time necessary to successfully participate and succeed in the course."

Course Grades

Student grades were computed from points earned on quizzes and tests, homework assignments, participation (as described in the Methodology section), and an optional research project. The optional project was a report on research into a topic of the student's choosing related to data communications and computer networks. Far more classroom students than online students completed the optional project (53% of classroom completers and 29% of online completers, $p=.038$).

At the beginning of the semester students were asked about their study habits in courses they had taken in the past. At the end of the semester they were asked about the study activities they had engaged in during the current course, and the difference between these two values was considered the extent to which students exerted more effort in the current course than in past courses. As noted earlier, this value was an important predictor of the grades students earned in the online course.

Online students who were more actively engaged in the learning activities of the current course than their *usual level of engagement in past courses* earned significantly higher course grades than students who did not change their learning behavior as much. As shown in Figure 10, online students who reported working harder in the current course than in prior courses earned higher grades than online students who reported working less. Although this was not statistically significant at the α=.05 level in the univariate model (shown in Figure 10), a linear regression model controlling for age, self-reported prior GPA, initial preference for interaction and performance on a pretest of domain knowledge indicated that the effort factor was statistically significant at the α=.01 level with a sample of only 18 cases (refer to Table 9). As shown in Figure 10, a similar increase in effort did not lead to higher grades for classroom students, however. In the A.I.S. classroom, effort was not strongly associated with course grades (p=.930). Online students tended to recognize the need to make more of an effort to be successful, and mentioned it in open ended responses asking them to give advice to other online students.

--- Figure 10 about here ---

--- Table 9 about here ---

Online students who made the effort to interact with their teacher and with other students through email and discussion boards also tended to earn higher course grades than students who did not make such an effort at communicating with others. However, as shown in Figure 11, more interaction with others was not associated with improved course grades for classroom students.

--- Figure 11 about here ---

Test Scores

In a similar way, online students who exerted more effort in the current course than in past courses also earned higher test scores and this was in marked difference to classroom students for whom extra effort did not make much difference in test scores. This difference is shown in Figure 12.

--- Figure 12 about here ---

Online students also recognized improvement in test scores associated with their level of interaction in the course, while classroom students did not recognize such gains as shown in Figure 13. Linear regressions controlling for initial preference for interaction, prior domain knowledge, age, and self-reported prior GPA (shown in Table 10) suggest that interaction matters most for online students (std. coeff. = .458, $p = .035$ for online students, std. coeff. = -.178, $p = .473$ for classroom students). The finding that interaction had only a modest effect on classroom students may be because it took very little effort for classroom students to interact with one another since class time was devoted to this each week. One conclusion we might draw from this difference between online and classroom students is that it is the *willingness to expend effort* to communicate with others that makes a difference in performance rather than the actual communication. Most students in the A.I.S. classroom course spent a significant amount of class time communicating with one another (i.e. about a third of the time), but this did not appear to improve their performance on course tests. Further investigation into the content of classroom student conversations could shed light on this difference, but online student communication, which was logged, indicated that their dialog was highly focused on relevant course topics.

--- Figure 13 about here ---

--- Table 10 about here ---

Conclusions

This study found evidence suggesting that course structure may be associated with academic performance while delivery mode may be associated with course completion. It also found that learner readiness characteristics can help explain how different groups of students might become more successful, particularly in their online courses.

Classroom students were about twice as likely as online students to complete their courses, although consistent reasons for students withdrawing from their online courses remain elusive. Since students in this study had the option of attending an evening section of the course (and there were two evenings to choose from), one might assume that those who chose the online section chose it primarily for convenience. There was some evidence suggesting that those who completed the online course were those who preferred working more independently, but the statistical evidence was not strongly compelling. The qualitative evidence may be more convincing: students reported that they withdrew from the online course because they discovered that they preferred a learning environment with a more physical connection to the teacher and to other students, or they found that they didn't have as much time as they needed to complete the course successfully.

It may be that students mistakenly believe they can squeeze an online course into an already full schedule because they do not have to make the trek to campus each week, and don't fully recognize the amount of effort that is required to compensate for what is missed by not attending class on a regular basis. In this study, the A.I.S. classroom course did not provide any additional course content or synthesis of material relative to the online course, but regular attendance in the classroom did expose students to the material for at least a few hours per week, which may have been more time than that invested by online students. Future research could investigate student's estimates of the time they actually spent on the course in the classroom and at home to get a better idea of whether this is the critical difference or not. Some online students who did not complete the course mentioned that once they got behind they just couldn't catch up.

This suggests that online teachers might help students by monitoring their participation and progress more diligently, particularly at the beginning of the semester. Although it may be common wisdom among educators, students may not realize what they miss by not attending a class in person each week. The amount of effort required to be successful in an online course could be spelled out to students, with an explanation as to the "teacher" roles online students must adopt.

Online students who exerted more effort in the current course than in past courses earned higher grades than students who exerted less effort, but "extra" effort was not as strongly associated with higher grades for classroom students. This suggests that classroom courses require a relatively uniform level of effort in learning activities, but to be successful in online courses students must expend more effort than they are accustomed to in classroom courses.

In addition, online students who interacted more with others in their course during the semester earned higher test scores than students who did not interact as much, and again interaction between students was not as strongly associated with higher test scores for classroom students. One possible explanation for this difference is that dialog among students and teachers in online courses is quite intentional; students have to make an effort to participate in a discussion forum or even to sit down and compose an email message to their instructors. On the other hand, dialog in the classroom is a more natural process, requiring little extra initiative for most students.

This study highlighted two paradoxes associated with online learning: 1) online students like to work alone, but earn higher grades when they interact with others, and 2) online courses require students to intentionally opt-in, but online students are more likely to opt-out. The design of any course sends a message to students. When the design of an online course is responsive to these paradoxes of online learning and can be customized to accommodate individual student preferences, we communicate to students our recognition and support of their unique needs.

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Appendix A

Perception of Course Relevance items
How important were the following factors in <u>deciding to take this course</u>? 1. This course provides General Education credit. 2. I am interested in this subject. 3. I wanted to take a course from this instructor. 4. I wanted to take this section because of when it is scheduled. 5. This course is necessary for my current job. 6. This course is necessary for my future career. 7. I want to get teacher guidance and feedback in this subject. 8. I want to have interaction with other students to discuss this subject. 9. I need the formal structure of a class to learn the material. 10. This course provides credit toward a degree or certificate. 11. I want to learn more about this subject or profession. 12. I need this course for my resume. 13. I need to pass this course so I can take a more advanced course in this subject.

Responsibility for Learning items
How have the following factors <u>contributed to your success</u> in previous courses? 1. The types of homework and projects assigned. 2. Feedback and guidance from the teacher. 3. My study habits. 4. The time I had available to study on my own. 5. My knowledge of using the Internet to access information **What are your usual <u>study habits</u>?** 6. I do my homework regularly. 7. I keep up with the reading assignments for my courses. 8. I am good at motivating myself to study regularly without being reminded by my teacher or someone else. 9. After taking a test, I like to check the book to see if I did some of the difficult problems correctly. 10. I like to explore a subject in more depth than what is required by my teachers (extra reading, online study, talk to other teachers, etc.).

Preference for Interaction items
How have the following factors <u>contributed to your success</u> in previous courses? 1. The teacher's lectures. 2. The availability of the teacher in his or her office or by email. 3. The participation/contributions of other students in the class. 4. The time I had available to meet with other students to study. **How do you usually <u>interact with your teachers</u>?** 5. I ask questions in class. 6. I volunteer to answer questions in class. 7. I meet with my teachers during office hours about the class. 8. I try to let my teachers know something about me as a person, such as my goals, my background, or what I hope to get from the course. 9. I communicate (talk, email, etc.) with my teachers about things not related to the specific course I'm taking with him or her. 10. My teachers are interested in me and my success in the class. **What are your usual <u>study habits</u>?** 11. I benefit from working with other students in the class. 12. I meet with other students outside of class time to study. 13. I communicate with other students by phone or email about the homework.

Affinity for Using Technology items
How do you use computers? 1. I check my email. 2. I use a word processor. 3. I use a spreadsheet or database program. 4. I play computer games on my own computer (or a friend's). 5. I play games on the Internet. 6. I access the Internet for school or work 7. I access news, weather, sports, stocks, etc. online. 8. I access the Internet for fun (other than games). 9. I participate in online chats 10. I participate in online conferences or bulletin boards. **How do you feel about the following uses of computers?** 11. I enjoy participating in online chats or conferences with other students from my classes. 12. I enjoy participating in online chats or conferences with people I may not know. 13. Online courses are a good alternative to classroom-based courses for people who can't get to a college campus. 14. Most college students could learn as much in an online course as in a classroom course.

Figures and Tables

Hardest to Endorse

This course is necessary for my current job.

I wanted to take a course from this instructor.
I need this course for my resume.
I want to have interaction with other students to discuss this subject.

I need the formal structure of a class to learn the material.

I want to get teacher guidance and feedback in this subject.

This course provides General Education credit.
I wanted to take this section because of when it is scheduled.
I need to pass this course so I can take a more advanced course
This course is necessary for my future career.
I want to learn more about this subject or profession.
This course provides credit toward a degree or certificate.
I am interested in this subject.

Easiest to Endorse

Figure 1: Perception of Course Relevance item calibrations.

Hardest to Endorse

I like to explore a subject in more depth than what is required.

My knowledge of using the Internet to access information

After taking a test, I like to check my answers.
The types of homework and projects assigned lead to my success.
Feedback and guidance from the teacher leads to my success.
I am good at motivating myself to study regularly

My study habits lead to my success.
I keep up with the reading assignments for my courses.
I do my homework regularly.
The time I had available to study on my own leads to my success.

Easiest to Endorse

Figure 2: Responsibility for Learning item calibrations.

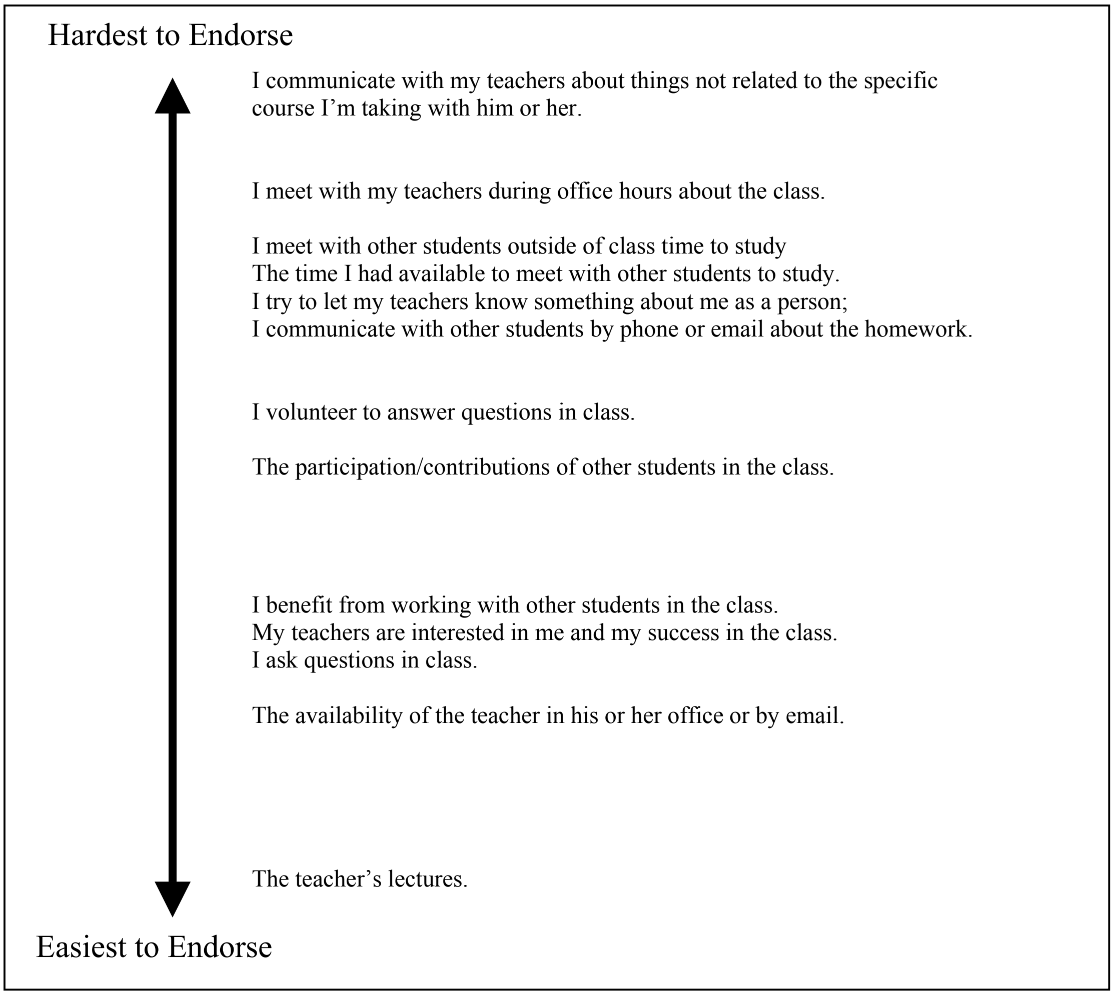

Figure 3: Preference for Interaction item calibrations.

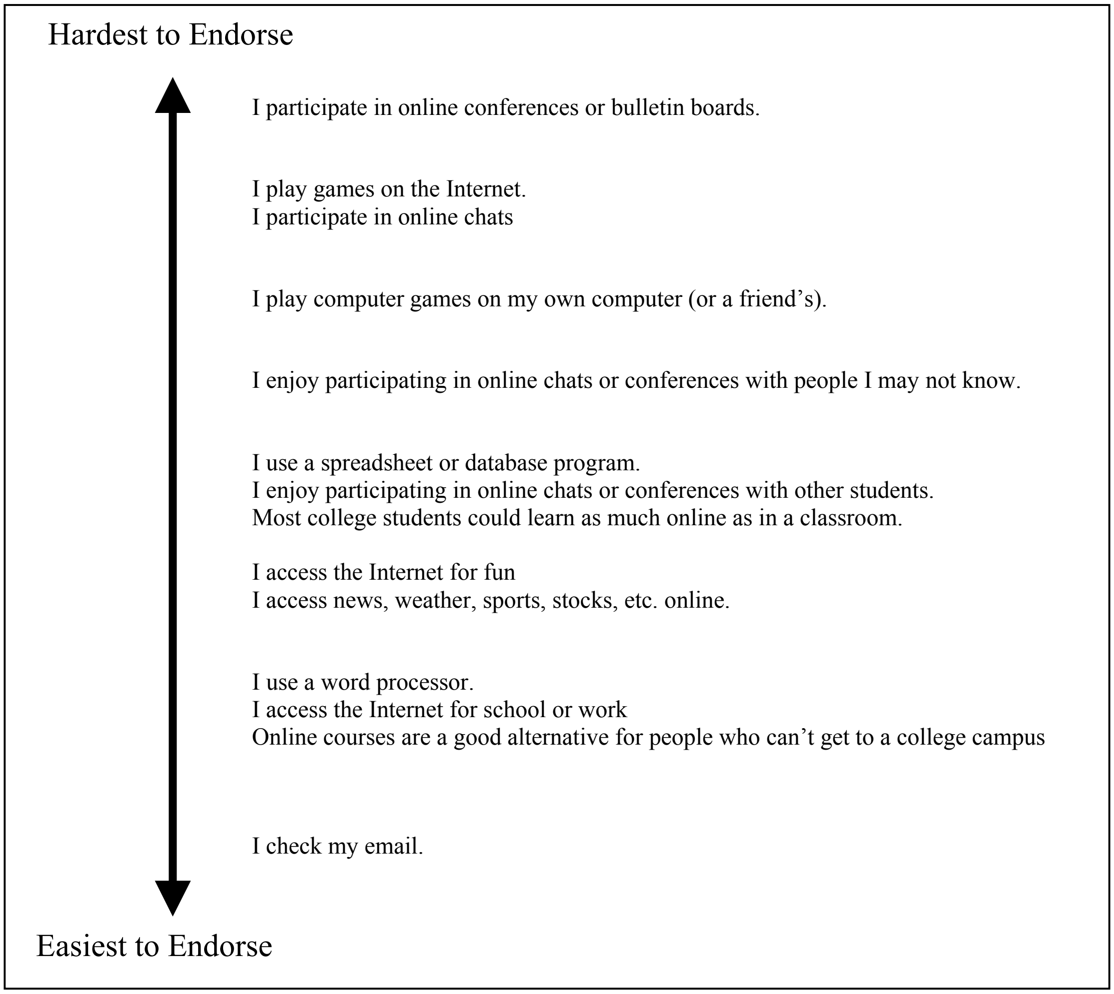

Figure 4: Affinity for Using Technology item calibrations.

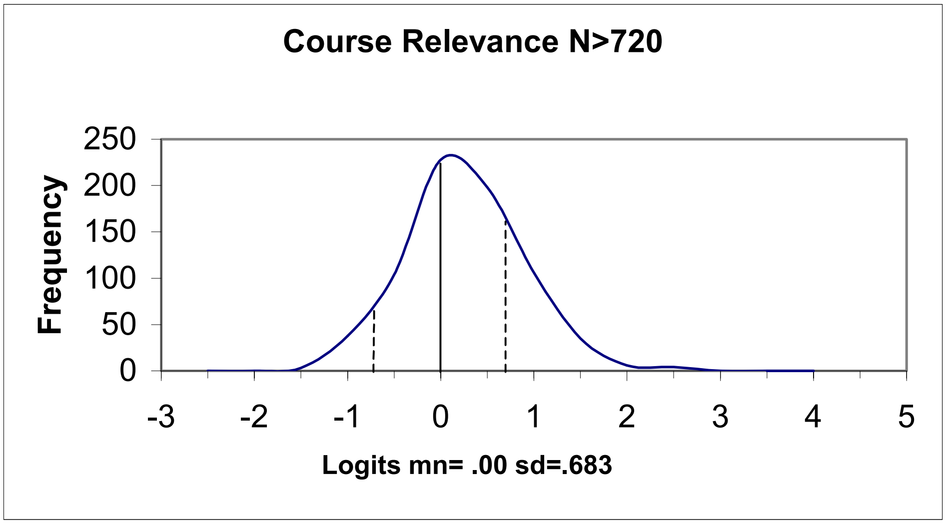

Figure 5: Frequency distribution of estimated student Perception of Course Relevance values with mean and +1 SD and -1 SD noted.

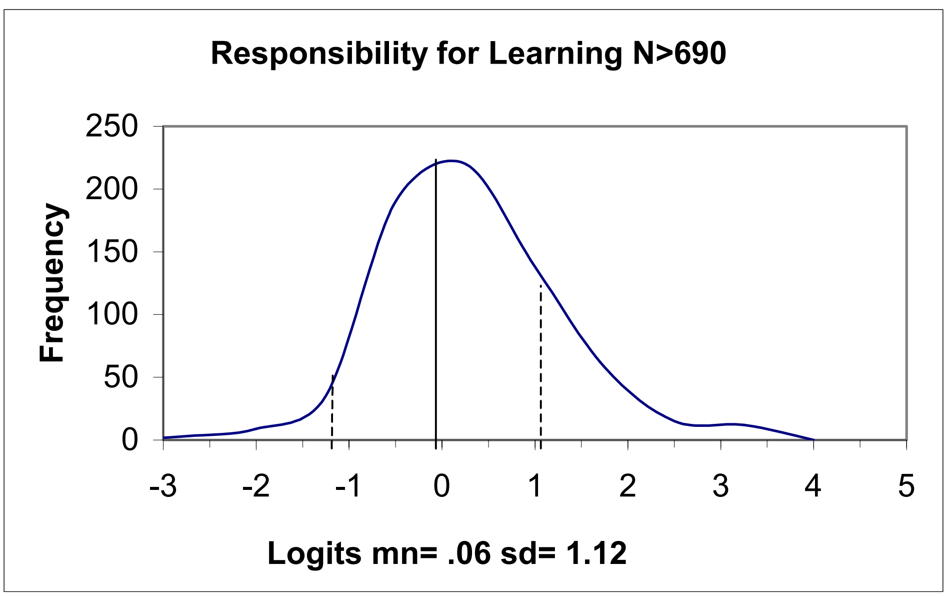

Figure 6: Frequency distribution of estimated student Responsibility for Learning values with mean and +1 SD and -1 SD noted.

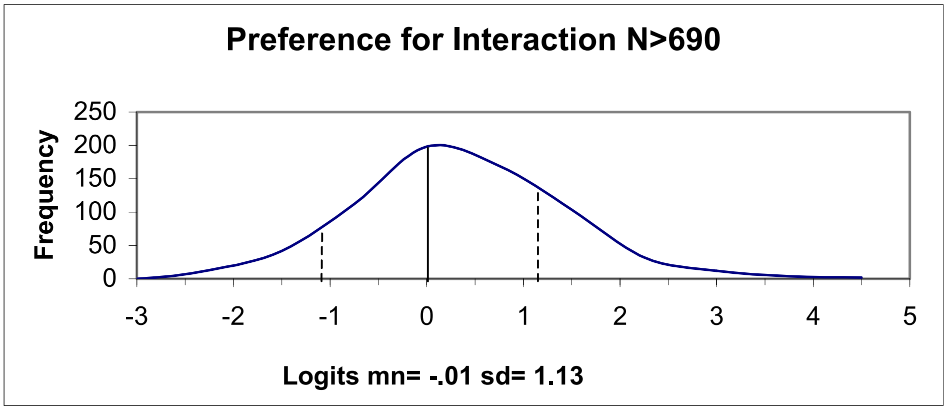

Figure 7: Frequency distribution of estimated student Preference for Interaction values with mean and +1 SD and -1 SD noted.

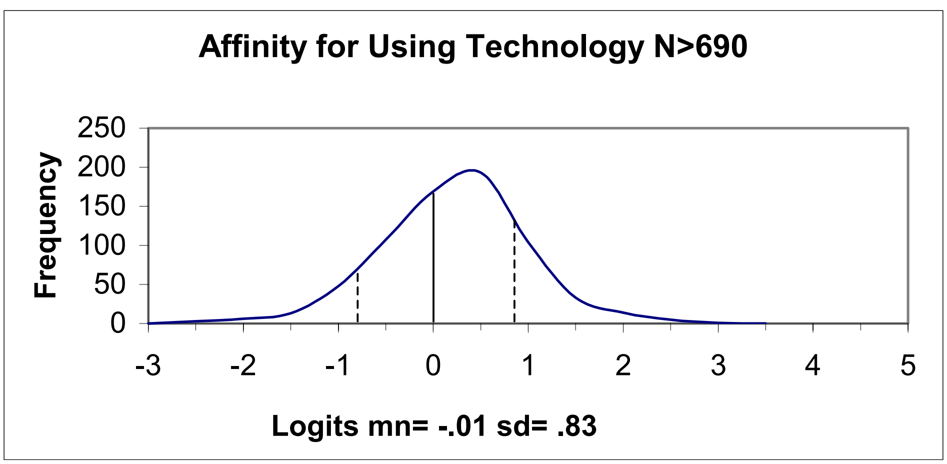

Figure 8: Frequency distribution of estimated student Affinity for Using Technology values with mean and +1 SD and -1 SD noted.

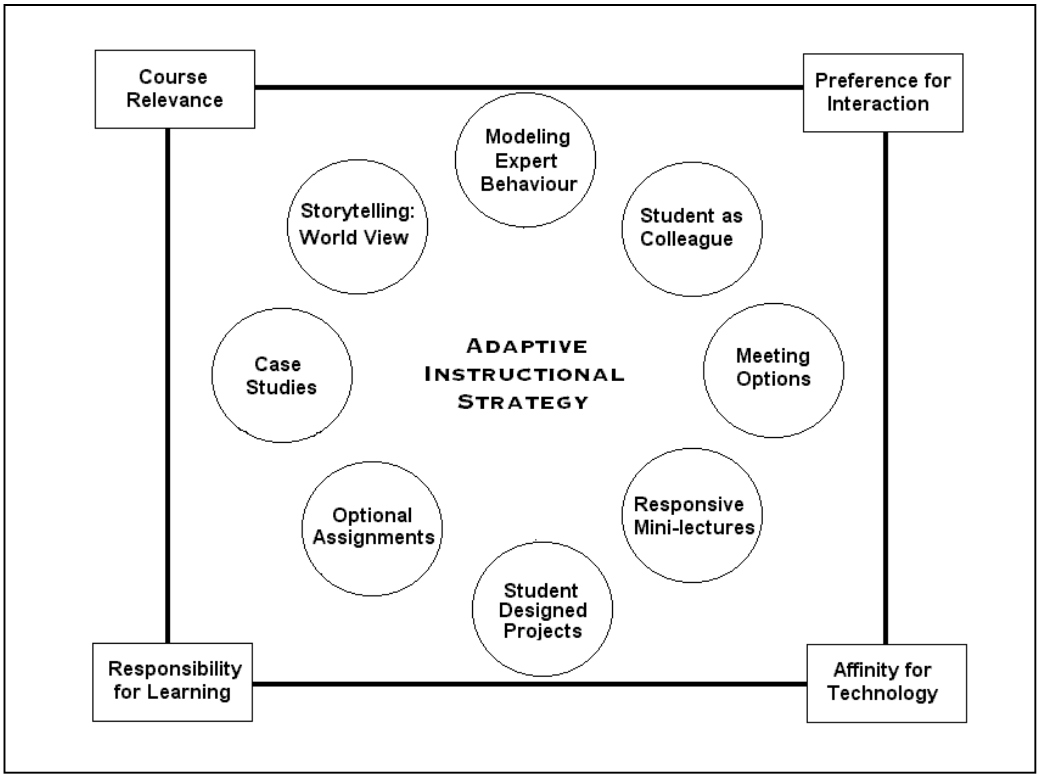

Figure 9: The Adaptive Instructional Strategy with consideration for Learner Readiness.

	N	Mean	S.D.	S. E.	Diff.	|t|	df	Sig.
Course grade								
Traditional	41	83.95	9.38	1.45	5.08	2.481	106	.015
A.I.S.	76	78.87	12.65	1.45				
Course tests								
Traditional	42	81.05	8.67	1.34	4.99	2.533	110	.013
A.I.S.	76	76.05	12.62	1.45				
Pretest								
Traditional	42	8.48	3.51	.54	0.24	0.363	105	.717
A.I.S.	64	8.23	3.25	.41				

Table 1: Independent means and t-test statistics comparing course grades, learning, and pretest scores for traditional and A.I.S. course structure groups.

Course Completion (N=158) controlling for first course in subject:

	1 Condition	2 Conditions
R^2	.097	.098
Std. Err.	.472	.473
F	8.341	5.598
Significance	< .001	.001
Std. Coeff. Online condition	-.213	-.197
Sig. Online condition	.006	.022
Std. Coeff. Structure condition	N/A	-.038
Sig. Structure condition	N/A	.657

Test Performance (N=83, completers only) controlling for age, GPA, pretest:

	1 Condition	2 Conditions
R^2	.273	.304
Std. Err.	9.390	9.250
F	7.417	6.817
Significance	< .001	< .001
Std. Coeff. Online condition	.024	.108
Sig. Online condition	.800	.306
Std. Coeff. Structure condition	N/A	-.198
Sig. Structure condition	N/A	.066

Course Grade (N=83, completers only) controlling for age, GPA, pretest:

	1 Condition	2 Conditions
R^2	.335	.366
Std. Err.	8.240	8.100
F	9.961	9.017
Significance	< .001	< .001
Std. Coeff. Online condition	-.095	-.012
Sig. Online condition	.302	.904
Std. Coeff. Structure condition	N/A	-.198
Sig. Structure condition	N/A	.054

Table 2 – Comparison of models with 1 Condition (online) and 2 Conditions (structure and delivery mode).

	Traditional mean	A.I.S. Classroom mean	A.I.S. Online mean	F	p
Preference for Interaction	.0180	.5061	-.1723	5.804	.004
Responsibility for Learning	.1431	.5938	-.0774	3.609	.029
Course Relevance	.4067	.3127	.0935	4.230	.016
Affinity for using technology	.1602	.1352	.4251	2.150	.127

Table 3: Means and ANOVA F-test statistics for learner readiness characteristic of students in all sections at start of term (after students were permitted to change sections), N=164.

	Pearson X^2	df	P
Gender	0.060	1	.807
Employment	0.519	2	.772
Age	4.525	7	.718
Grade point average	3.536	5	.618
First course in subject	1.275	1	.259
Units Completed	6.000	3	.112

Table 4: Univariate chi-square statistics for categorical variables, students in online and classroom A.I.S. sections at start of term.

	AIS Class. means	Online means	Diff.	|t|	Sig.
Pretest Score	7.95	8.35	-.4000	0.551	.583
Learner Readiness Characteristics					
Preference for Interaction	.5061	-.1723	.6784	3.163	.002
Responsibility for Learning	.5938	-.0774	.6713	2.513	.013
Course Relevance	.3121	.0093	.3027	2.173	.032
Affinity for using tech.	.1244	.4251	-.3007	1.923	.057

Table 5: Initial means and t-test statistics for quantitative variables, classroom and online A.I.S. students at start of term.

X^2 =18.068, df = 7, p = .0117, N=77

	B	S.E.	Wald	df	p
Predictor:					
Affinity for using technology	1.1058	.4560	5.8812	1	.0153
Preference for interaction	-.7172	.3298	4.7300	1	.0296
Perception of course relevance	-.5604	.3874	2.0927	1	.1480
Responsibility for learning	-.1960	.2546	.5923	1	.4414
Controlling for:					
Age	.1257	.1766	0.5066	1	.4766
GPA	.2659	.2585	1.0577	1	.3037
Pretest score	-.0035	.0729	0.0023	1	.9617

Table 6: Binary logistic regression of selecting the online course on readiness characteristics for classroom and online A.I.S. starters, controlling for age, GPA, and pretest score.

$X^2 = 14.606$, df = 3, p = .0022, N=109

	B	S.E.	Wald	df	p
Predictor:					
Online delivery mode	-.8124	.4192	3.7565	1	.0526
Controlling for:					
First course in subject	.8113	.4167	3.7895	1	.0516
Affinity for using technology	-.4861	.2605	3.4828	1	.0620

Table 7: Binary logistic regressions of course completion on course delivery mode, controlling for first course in subject and affinity for using technology.

$X^2 = 9.97$, df = 5, p = .076, N=58

	B	S.E.	Wald	df	p
Predictor:					
Preference for interaction	-.9918	.4973	3.9774	1	.0461
Responsibility for learning	.5944	.3650	2.6524	1	.1034
First Course in Subject	-1.2173	.7720	2.4865	1	.1148
Perception of course relevance	.8134	.6207	1.7172	1	.1901
Affinity for using technology	-.0486	.6726	0.0052	1	.9424

Table 8: Binary logistic regression of course completion on readiness characteristics and whether course was first taken in the subject for online A.I.S. starters.

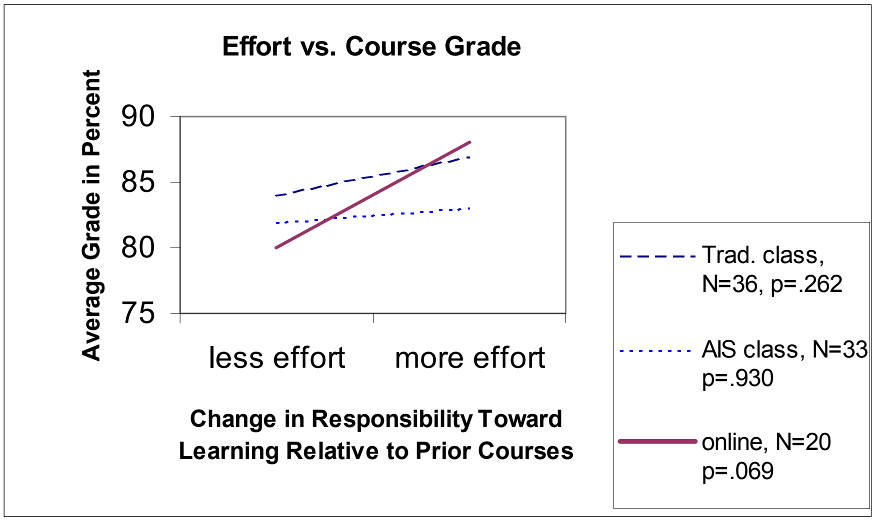

Figure 10: Relationship of effort expended in learning activities, relative to past courses, to course grade for classroom and online students.

$R = .886$, $R^2 = .786$, Adj. $R^2 = .704$, $p = .001$, $SE = 6.40$, $N=18$

	Coeff.	Std. Coeff.	|t|	p
Predictor:				
Change in Responsibility	5.148	.474	3.542	.004
Controlling for:				
Age	4.048	.579	3.825	.002
GPA	1.542	.164	1.180	.259
Pretest score	.586	.196	1.436	.175
Initial preference for interaction	.224	.020	0.145	.887

Table 9: Regression of course grades over change in responsibility for learning for online A.I.S. students who completed, controlling for age, gpa, pretest score, and pref. for interaction.

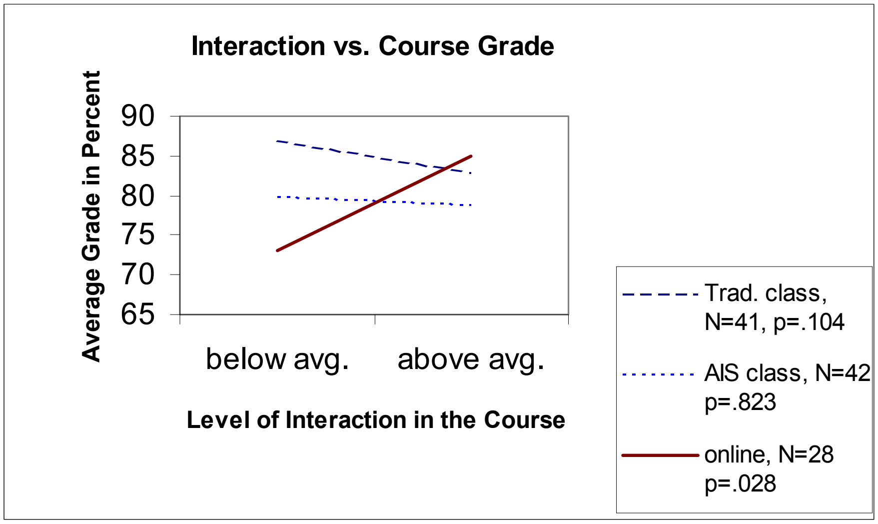

Figure 11: Relationship of interaction with others to course grades for classroom and online students.

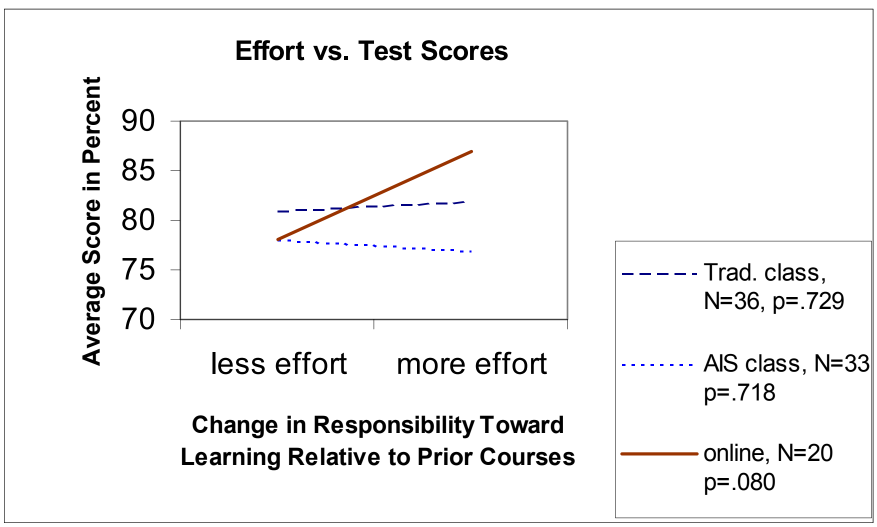

Figure 12: Relationship of effort expended in learning activities, relative to past courses, to test scores for classroom and online students.

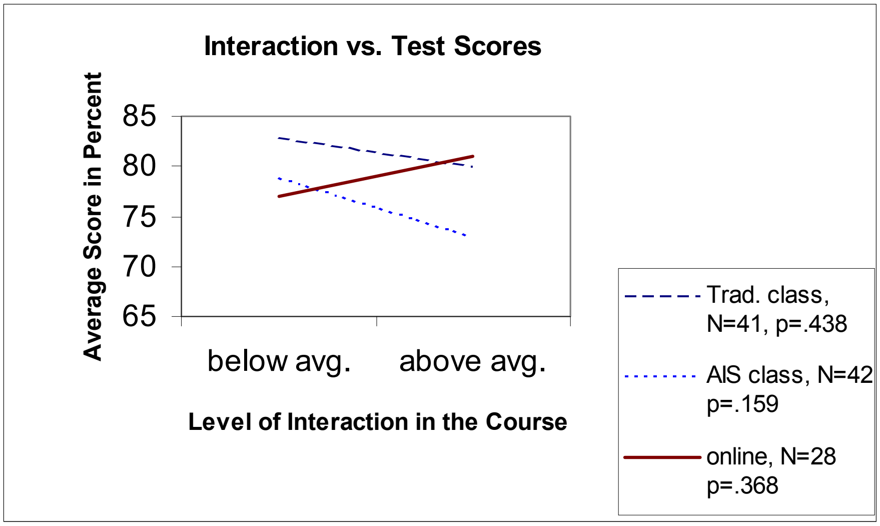

Figure 13: Relationship of interaction with others to course grades for classroom and online students.

$R = .820$, $R^2 = .673$, Adj. $R^2 = .547$, $p = .007$, $SE = 8.56$, $N=18$

	Coeff.	Std. Coeff.	|t|	p
Predictors:				
Interaction in this course	2.458	.458	2.359	.035
Controlling for:				
Age	4.258	.563	3.016	.010
GPA	-.344	-.034	0.174	.865
Pretest score	.721	.223	1.333	.205
Initial preference for interaction	-2.865	-.241	1.369	.194

Table 10: Regression of test scores over interaction for online A.I.S. students who completed, controlling for age, gpa, pretest score, and initial pref. for interaction.