Predicting Success for Virtual School Students: Putting Research-based Models into Practice

M. D. Roblyer
University of Tennessee
margaret-roblyer@utc.edu

Lloyd Davis
University of Tennessee
lloyd-davis@utc.edu

Abstract

Virtual schooling has the potential to offer K-12 students increased access to educational opportunities not available locally, but comparatively high dropout rates continue to be a problem, especially for the underserved students most in need of these opportunities. Creating and using prediction models to identify at-risk virtual learners, long a popular topic in distance education, is assuming increasing urgency in virtual schooling. Though many studies have tested the contributions of various factors to online success, this article emphasizes that prediction models must be developed and used in ways that yield findings to support student success rather than prevent students from enrolling. One such model is offered here. After a description of data collection and statistical processes used to derive the model, procedures are outlined for how to implement it in virtual school settings in ways that increase both the accuracy and utility of predictions.

Introduction: A Rationale for Predicting Performance

The Quest for a Success Prediction Model: Popular and Problematic

The early promise of virtual schooling (school courses offered through distance technologies) was to provide access to high-quality educational opportunities for students who traditionally lack such opportunities: rural, underserved, and at-risk populations (Davis & Roblyer, 2005). However, there are indications that virtual schooling opportunities tend to benefit primarily already-advantaged learners (Roblyer & Marshall, 2003; Roblyer, et. al, 2008). Growing numbers of middle and high school students are taking virtual courses (Watson & Ryan, 2007), but compared to traditional in-person courses, virtual school courses almost always reflect higher student failure and dropout rates (Kozma & Zucker, 2003), a finding consistent with those from postsecondary populations (Bernard et al., 2004).

While virtual schools are being founded to provide access to educational opportunities not locally available (Roblyer, Freeman, Mason, & Schneidmiller, 2007; Watson & Ryan, 2007) Hartley and Bendixen (2001) point out that that educational access does not equate to educational opportunity. For example, in at least one large virtual school, minority students tended to enroll less but drop out more (Florida TaxWatch, 2007). Hartley and Bendixen are among those who feel that certain cognitive characteristics (e.g., lack of self-regulation) could predetermine low performance in distance environments. Thus, the desire to identify and, if possible, support at-risk virtual learners in ways that increase chances for their success has generated considerable interest among virtual schools.

However, the quest for a prediction model to identify at-risk virtual learners has proven problematic. Studies have hypothesized and identified a variety of student and environmental characteristics that contribute to success, but no one set of characteristics has emerged as dominant and none of the studies that offered a model has offered an efficient way to apply its findings in practice. A recent study reported in Roblyer, Davis, Mills, Marshall, and Pape, (2008) has produced a prediction model that helps explain variations in previous findings and lends itself to practical implementation. While the Roblyer, et al. article emphasized how and why the model was generated, the information reported here focuses on how the model they created could be used in practice to help identify students who may need additional assistance in order to be successful in virtual environments.

Background: Studies of Contributors to Persistence in Distance Courses

Though it has long been acknowledged that distance courses have the potential to offer educational opportunities of equivalent quality to in-person courses (the so-called "no significant differences phenomenon" reported by Russell (2001) and others), research findings also consistently confirm that failure and dropout rates are higher in distance environments (Bernard & Amundsen 1989; Cyrs 1997; Dille & Mezack 1991). As the problem of low retention rate in distance environments became apparent over the years, a variety of studies emerged to explore the causes (see Table 1 at end of article). Lines of research on characteristics of successful learners took several forms, including: identifying demographic and psychological characteristics that were predictors of success, creating and testing retention models based largely on learner characteristics, and developing instruments to identify at-risk distance learners.

Other researchers hypothesized factors other than learner characteristics that were also important contributors to success. Smith and Dillon (1999) and Chyung (2001) felt that the way distance learning delivery systems were designed and configured could explain much of the variance in comparisons of performance in distance and traditional environments. Of particular interest were studies that found that providing better social and emotional support to reduce what Woolcott (1996) referred to as "psychological distance" could reduce attrition. Frankola (2001), Willgin and Johnson (2004), Bocchi, Eastman, and Swift (2004) and Santaovec (2004) all found that factors with most influence on decisions to drop out of distance courses had to do with “issues of isolation, disconnectedness, and technological problems” (Frankola, 2001, p. 53). They believed that, if course environments were designed to increase facilitation, communication, and feelings of connectedness to a learning community, dropout rate would decrease. However, in light of the fact that so many students are successful in the same courses in which others drop out, it seems likely that some students require even more facilitation and monitoring than others in virtual courses.

A Rationale for Studying Success Prediction

The rationale underlying studies of both learner and learning environment characteristics is that effective strategies are needed to help organizations increase student success and reduce dropout rates in distance courses. Since it makes intuitive sense that a combination of these factors contribute to success, a model is needed that has two essential qualities: (1) it is based on the combined factors that research indicates could contribute to predicting success, and (2) it would itself to efficient measurement and implementation in virtual school settings.

Creating and using such a model is assuming increasing urgency in virtual schooling. Recent reports confirm that it has become one of the fastest-growing international trends in education today (National Forum, 2006; Setzer, Lewis, & Green, 2005; Zandberg & Lewis, 2008). States are increasingly looking to online strategies and resources to provide students with courses not available locally and to allow accelerated or remedial alternatives for students who need them. The recent National Center for Education Statistics' report (Zandberg & Lewis, 2008) found that in 2004–05, there were an estimated 506,950 technology-based distance education course enrollments in public school districts. "Ten percent of all public schools nationwide had students enrolled in technology-based distance education courses during 2004–05, an increase from 9 percent in 2002–03" (p. iv). Based on these findings, the report observed that "technology-based distance education has established its presence in the nation’s public schools" (p. ix).

Despite anticipated and real benefits of virtual schooling, it is not unusual for virtual schools to report a dropout rate of from 40-70% (Oblender, 2002; State of Colorado, 2006), though some established schools claim a dropout rate from 10-20%. In the case of one program, it was found that virtual students were forced to repeat grades at a rate four times that of students statewide (Rouse, 2005). Some virtual school programs have addressed high dropout and failure rates through front-end means such selecting and admitting students on the basis of identified criteria, instituting required pre-course orientations, and increasing the length of the drop-add period to 28 or more days. Some schools have also increased levels of students monitoring and facilitation. Virtual schools report no data on the success of the latter strategies, but informal reports indicated they have met with at least some success (Pape, Revenaugh, Watson, & Wicks, 2006).

As the virtual schooling movement gains momentum and states increase their virtual schooling offerings, virtual school populations will increase in both size and diversity of students. Equal opportunity and equity requirements will make it impossible for most schools to select only certain students to take online courses, so the emphasis will be on strategies to support students in ways that help promote retention and success in virtual courses.

However, using such models in typical virtual school settings presents formidable obstacles. Not only must such a model offer valid and reliable predictors of success, procedures to implement it must be efficient and lend themselves to quick identification of and interventions for at-risk students. Its use should identify students for specific kinds of extra assistance, but not emphasize factors that would be difficult to address or take so long to employ that, in essence, it prevents at-risk students from enrolling, rather than promoting their success once they do sign up. Thus, creating prediction models presents challenges from both a theoretical research standpoint, as well as from practical and logistical ones.

The next part of this article describes a model created by Roblyer, et al. (2008) that could help meet these challenges. After a description of the data collection and statistical procedures Roblyer, et al. used to derive the model, procedures will be described for how to implement it in virtual school settings.

Methodology and Findings from the Roblyer, et al. Success Prediction Study

As previously reported in Roblyer, et al. (2008), a study was done using a revision of a Likert scale instrument used in earlier studies by Roblyer and Marshall (2002-2003): the Educational Success Prediction Instrument (ESPRI). In this survey, students are asked to rate their degree of agreement or disagreement with statements such as "I believe myself to be a high achiever." Although Roblyer and Marshall found that the instrument was successful in a small-scale field test, a subsequent field test found much more variability and recommended further testing with larger populations.

To derive a more comprehensive and useful model for addressing virtual school success issues, the Roblyer/Marshall instrument was modified based on past factor analysis and logistical regression findings, as well as a review of the increasingly diverse literature in this area. Several items related to student background (e.g., self-reported GPA), as well as online learning environment (e.g., home computer access, availability of a school period set aside for VS course work) were added to the survey to produce a 60 Likert scale item instrument that addressed each of five hypothesized factors: organization, achievement beliefs, responsibility, risk-taking, and technology skills/access.

Subjects in the study were 4,110 students in the Virtual High School Global Consortium (VHS) who were enrolled in 196 VHS courses during the Spring, 2006, semester. Over 80% of VHS member schools were from rural and suburban locales, and 27% of VHS member schools were Title I eligible schools. An electronic version of the instrument was placed in the course spaces of all VHS courses enrolled during the Spring, 2006 semester. Students were offered 10 points extra credit on their first week's assignments to complete the survey. A completed ESPRI survey, demographic data, and course scores and status were obtained for 2,162 students or about 53% of the total school population for the semester, although most of the 2,880 students completed all but one or two of the items.

Data Analysis Methods

To determine the combination of *ESPRI* items, background characteristics, and educational factors that could best predict success/failure in virtual courses, Roblyer, et al (2008) performed several analyses, including: descriptive statistics and frequency distributions, factor analyses, whole-instrument and component scale reliabilities, logistical regression, and calculations to determine success/failure probabilities based on contributing factors. For the purposes of this study, students who completed a course with a grade of A, B, or C grade were identified as successful (or passing). Students who dropped or withdrew from the course or completed it with a grade of D, F, I, or W were labeled Failed. Applying this pass/fail criterion, 1,994 or 75% of high school students passed the virtual course and 665 cases or 25% of high school students failed the course.

Factor Analysis and Reliability Results

Since online instructors and administrators had observed that online students would be more likely to complete an abbreviated instrument, a factor analysis was done to determine if the number of items could be reduced while maintaining good reliability and maximizing explained variance among items. A principal components extraction method with varimax rotation was used on the 60 ESPRI items, since the purpose was data reduction, as well as exploration of the proposed model (Fabrigar, Wegener, MacCallum, & Strahan, 1999). The 25 items that resulted from this factor analysis loaded on four factors: technology use and technology self-efficacy (10 items), achievement beliefs (6 items), risk-taking (6 items), and organization strategies (3 items). Since the responsibility factor was seen as having substantial overlap with achievement beliefs, the resulting set of variables and factors was viewed as representing a logical model in terms of theory and previous findings. Reliability with the 25-item instrument was .92.

Results from Logistical Regression Analysis

A binary logistic regression analysis with pass-fail status as the dependent variable was done to test the model hypothesized to predict success since this was an exploratory study, various combinations of factors were tried, including all the student background factors that were significantly different between the pass and fail groups, as well as the sums of individual ESPRI factors and the sum of scores from the 25-item *ESPRI*.

The goal of this analysis was to obtain a combination of factors that yielded the best prediction of success and failure. However, successive analyses found that each of the combinations always yielded much better success prediction than failure prediction. The best combination of variable that maximized both success and failure prediction was: the ESPRI sum (across 25 items), two student background variables (age and self-reported GPA), and two environmental variables (home computer availability and school period for working on the virtual course) with a cutoff value of 0.6 and an alpha of .05. As shown in Table 2, the model correctly predicted 93% of those who were successful, but only 30.4% of those who failed.

Table 2

Classification Table from Logistic Regression

	Predicted Fail	**Predicted Pass**	**Totals**
Actual Fail	**143 (30.4%)**	328 (69.6%)	471 failed
Actual Pass	119 (7.0%)	**1572 (93.0%)**	1691 passed

79.3% of original grouped cases correctly classified. (Obtain this by adding 143 + 1572 or the number correctly classified divided by the total sample of 2162.)

Procedures for Using Success Prediction Models in Practice

Results from a model that can predict success over 90% of the time also provide an opportunity for using the model efficiently in practice. This strategy is based on the odds ratios that result from a logistical regression, as described above. After a description of the statistical procedure for using odds ratios to predict success probabilities, we describe how schools might implement a success-prediction system and use the results to drive pre-course interventions.

Procedures for Calculating Probabilities

Table 3 shows odds ratios resulting from the survey, as well as regression coefficients, Wald statistics, and 95% confidence intervals for each of the five predictors. For the data derived in this study, all five variables were contributors to the prediction model, though relationships were moderate. Note that Roblyer, et al. (2008) included age as a factor, even though it was not significant, since it was obviously a contributor and, thus, increased the usefulness of the model. The Odds Ratios tells us that for a 1 unit change in the variable, the odds change for that variable by the stated odds ratio factor. For example, having a computer at home and an assigned class period to work on virtual course increase a student’s odds of success by 2.663 and 1.906, respectively. This means that such a model, where success prediction is maximized, lends itself to an easy means of using it in practice. Though it would be good if a "yes/no" prediction were possible, but in fact, any prediction of human behavior must be in terms of probabilities. This model makes it possible to do estimates of probabilities for success.

Table 3

Logistic Regression Analysis of Pass/Fail Status as a Function of Derived Variables

	B	**Wald Chi Square**	**Odds Ratios**	**95% Confidence Interval**	
Variables				**Lower**	**Upper**
ESPRI Sum (25)	-.005	5.398	.995	.990	.999
VHS class time	.645	19.273	1.906	1.429	2.543
Home computer	.980	16.716	2.663	1.665	4.259
Age	.098	3.468	1.103	.995	1.223
GPA	1.225	192.546	3.509	2.939	4.189
Constant	-4.443	21.295	.012		

The following steps show a statistical procedure for using the information resulting from the logistical regression to calculate success probabilities. First, the logistical equation resulting from the logistic regression is shown below in Table 4. ESPRI and other measures (e.g., observed GPA) can be inserted into the equation to determine students’ probability of success and failure.

Table 4

Logistic Regression Coefficients and Sample Data to Use in the Equation

	ESPRI25	VHSTime	HmComp	Age	Grade Avg.	Constant	Sum of reg.	Pr(obs event)
Regression Coefficients	-0.005	0.645	0.98	0.098	1.255	-4.443		
Sample Data	40	1	1	14	1		-0.391	0.403

The logistic equation shown below can be used to calculate a Probability of Passing (POP) score for each student. The two-step procedure is show below, using the sample data in Table 4:

1. $$Expression = 1 + e^{-(\alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5)}$$

2. $$p\_ob(event) = \frac{1}{Expression}$$

Step 1. The following coefficients for the variables to be used in the equation were obtained from the variables in the logistic regression output (Table 4):

$$\alpha = -4.443, \beta_1 = -.005, \beta_2 = .645, \beta_3 = .98. \beta_4 = .098 \ \& \ \beta_5 = 1.255$$

Using this equation on sample data (shown in row 2 of Table 4), if an individual has an ESPRI sum of 40 (based on the way Likert items are set up, lower scores are better), a virtual classroom class period assigned at school, a computer at home, is 14 years of age, and has C or D self reported grade point average, the following vector X is constituted:

$$X_1 \text{ (ESPRI)} = 40, X_2 \text{ (Time)} = 1, X_3 \text{ (Computer)} = 1, X_4 \text{ (Age)} = 14, \text{ and } X_5 \text{ (GPA)} = 1$$

Step 2*:* Inserting these values for X and using the regression coefficients a and bs above, yields a probability of .403 that the individual will pass. In this case since the probability is less than 0.6 (cutoff value), we would predict failure. Probabilities of passing are able to be calculated in this way for students with any combination of these factors.

Procedures for Implementing the Model in Practice

Generating probability estimates. Using this procedure, schools can calculate a Probability of Passing score for any given student. Virtual school personnel can use a given student's combination of characteristics to determine that student's probability of being successful in virtual environments.

Once a Probability of Passing model is put into electronic format, for example, on a website, it could yield a quick calculation of success probabilities. Virtual schools would have to decide which probability they would feel comfortable accepting without any special intervention, e.g., 70-80% or higher. Any student with a lower probability of success could then be targeted for a greater degree of monitoring and facilitation. Further, since students who will drop out are more likely to do so in the early weeks of the course (Chyung, 2001), virtual school personnel can emphasize monitoring more in the early weeks.

Using the model's output. The same electronic system that calculates Probability of Passing scores could also be designed to yield other information, which virtual schools and parents/guardians could then use to support success for at-risk students. For example, it is likely that students who score low on the ESPRI survey lack organization skills and online self-efficacy. Specific pre-course interventions could be made available to address these deficits. Past studies have found, for instance, that orientation sessions for distance learners can make a significant contribution to success (Wojciechowski & Palmer, 2005). Orientations that specifically address how to organize and work in online environments could be especially useful to at-risk students.

Other studies found that students who had good study environments (i.e., a place to complete online work) (Osborn, 2001) or additional facilitator support during courses (Frid, 2001) were less likely to drop out. If, as the Roblyer et al. (2008) study found, having a home computer contributed greatly to students' success, arrangements could be made for outside-school times for students to have access to computers. Each contributing factor could be matched to appropriate interventions. Although factors such as age and maturity could not be addressed (at least, not immediately), the number of other contributing factors makes it unlikely that non-malleable factors (e.g., age) alone would determine students' success or failure.

Implications and Recommendations for Future Work

Future uses of a success prediction system. Findings from previous studies indicate that a combination of student factors and learning conditions can predict success of high school students in virtual environments, though predicting success will probably be much easier than predicting failure. However, it seems unlikely that the results of findings from the model reported here, based as it was on data from a population that is 77% Caucasian and has a comparatively low dropout/failure rate, would be of use with a virtual school with high minority enrollment and higher dropout and failure rates. Rather, it seems likely that a set of factors specific to the school's population must be generated in order to calculate meaningful Probability of Passing scores for the students. Further, the emphasis in future studies should be on obtaining data (e.g., GPA) that could be confirmed as accurate, rather than relying on student's self-reported data.

Emphasizing procedures that foster success, rather than block registration. It is important to note here that past studies that hypothesize that the most important contributors to virtual course success are student characteristics that cannot be changed through intervention are less than useful. Such studies could set the stage for preventing students of lower abilities from taking virtual courses at all. This outcome that would keep virtual schools from making important contributions to building a better, more equitable and effective educational system. Thus, while researchers like Hartley and Bendixen (2001) emphasize the role of student characteristics such as past achievement, which set limits on who will be able to take advantage of online educational opportunities, the study reported here provides intriguing and hopeful support for the view that we can do more than we are currently doing to assure success for all students, even those who have known deficits in past achievement and self-regulation. With functional strategies in place to identify and assist at-risk virtual learners, virtual schools can better fulfill their early promise of becoming an education equalizer.

References

Aronson, J., & Timms, M. (2003). *Net choices, net gains: Supplementing the high school curriculum with online courses.* WestEd Knowledge Brief. Retrieved November 1, 2003, from http://www.wested.org/online_pubs/KN-03-02.pdf

Bernard, R., & Amundsen, C. (1989). Antecedents to dropout in distance education: Does one model fit all? *Journal of Distance Education, 4*(2), 25-46.

Bernard, R., Brauer, A., Abrami, P., & Surkes, M. (2004). The development of a questionnaire for predicting online learning achievement. *Distance Education, 25*(1), 44-47.

Bernard, R., Abrami, P., Lou, Y., Borokhovski, E., Wade, A., Wozney, L., Wallet, P., Fiset, M., & Huang, B. (2004). How does distance learning compare with classroom instruction? A meta-analysis of the empirical literature. *Review of Educational Research, 74*(3), 379-434.

Bocchi, J., Eastman, J., & Swift, C. (2004). Retaining the online learner: Profile of students in an online MBA program and implications for teaching them. *Journal of Education for Business, 79*(4), 245-253.

Cheung, L., & Kan, A.(2002). Evaluation of factors related to student performance in a distance learning business communication course. *Journal of Education for Business, 77*(5), 257-263.

Chyung, S. (2001), Systematic and systemic approaches to reducing attrition rates in online higher education. *The American Journal of Distance Education, 13*(3), 36-49.

Cyrs, T. E. (1997). Competence in teaching at a distance. In *Teaching and learning at a distance: What it takes to effectively design, deliver, and evaluate programs, ed.* T. E. Cyrs. San Francisco: Jossey-Bass.

Cyrs, T.E. (1997). *Teaching and learning at a distance: What it takes to effectively design, deliver, and evaluate programs.* San

Francisco: Jossey-Bass.

Davis, N., & Roblyer, M. D. (2005). Preparing teachers for the "schools that technology built": Evaluation of a program to train teachers for virtual schooling. *Journal of Research on Technology in Education*, *37,* 399-409.

DeTure, M. (2004). Cognitive Style and Self-efficacy: Predicting student success in online distance education. *American Journal of Distance Education, 18*(1), 21-38.

Dickson, P. (2005). *Toward a deeper understanding of student performance in virtual high school courses: Using quantitative analyses and data visualization to inform decision making.* Naperville, Illinois: NCREL/Learning Point Associates.

Dille, B., & Mezack, M. (1991). Identifying predictors of high risk among community college telecourse students. *The American Journal of Distance Education*, *5*(1), 24-35.

Dupin-Bryant, P. (2004). Pre-entry variables related to retention in online distance courses. The *American Journal of Distance Education*, *18*(4), 199-206.

Dweck, C. (1986). Motivational processes affecting learning. *American Psychologist, 41*, 1040-1048.

Education Week (2005). *Technology Counts 2005*. Available online at http://www.edweek.org/ew/toc/2005/05/05

Fabrigar, L., Wegener, D., MacCallum, R., & Strahan, E. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, *4*(3), 272-299.

Florida TaxWatch Center for Educational Performance and Accountability. (2007). *Final report: A comprehensive assessment of Florida Virtual School*. Tallahassee, Florida. Available at: http://www.floridataxwatch.org/resources/pdf/110507FinalReportFLVS.pdf

Frankola, K. (2001). Why online learners drop out. *Workforce, 80* (10), 53.

Frid, S. (2001). Supporting primary students' on-line learning in a virtual enrichment program. *Research in Education*, *66*, 9-27.

Gibson, D., & Graff, A. (1992). Impact of adults' preferred learning styles and perception of barriers on completion of external baccalaureate degree programs. *Journal of Distance Education, 7*(1), 39-51.

Hartley, K., & Bendixen, L. (2001). Educational research in the Internet age: Examining the role of individual characteristics. *Educational Researcher*, *30*(9), 22-26.

Lim, C. (2001). Computer self-efficacy, academic self-concept, and other predictors of satisfaction and future participation of adult distance learners. *The American Journal of Distance Education, 15*(2), 41–52.

Loomis, K. (2000). Learning styles and asynchronous learning: Comparing the LASSI model to class performance. *Journal of Asynchronous Learning Networks, 4*(1), 23-31.

Maki, W., & Maki, R. (2002). Multimedia comprehension skill predicts differential outcomes in web-based and lecture courses. *Journal of Experimental Psychology, 8*(2), 85-98.

Menlove, R., & Lignugaris-Kraft, B. (2004). Preparing rural distance education preservice special educators to succeed. *Rural Special Education Quarterly, 23*(2), 18-26.

National Forum on Educational Statistics. (2006). *Forum guide to elementary/secondary virtual education (NFES 2006-803).* U. S. Department of Education. Washington, DC: National Center for Education Statistics.

Oblender, T. (2002). A hybrid course model: one solution to the high online drop-out rate. *Learning and Leading with Technology, 29* (6), 42-46.

Osborn, V. (2001). Identifying at-risk students in videoconferencing and web-based distance education. *The American Journal of Distance Education, 15*(1), 41-54.

Pape, L., Revenaugh, M., Watson, J., & Wicks, M. (2006). Measuring outcomes in K-12 online education programs: The need for common metrics. *Distance Learning, 3*(3), 51-58.

Parker, A. (2003). Identifying predictors of academic persistence in distance education. *USDLA Journal, 17*(1). Available at: http://www.usdla.org/html/journal/JAN03_Issue/index.html

Pillay, H., Irving, K., & McCrindle, A. (2006). Developing a diagnostic tool for assessing tertiary students readiness for online learning. *International Journal of Learning Technology, 2*(1), 92-104.

Roblyer, M. D. (2003). Virtual high schools in the United States: Current views, future visions. In The open classroom: Distance learning in and out of schools, ed. Jo Bradley. London: Kogan Page.

Roblyer, M. D., Davis, L., Mills, S., Marshall, J., & Pape, L. (2008). Toward practical procedures for predicting and promoting success in virtual school students. *The American Journal of Distance Education, 22*(2), 90-109.

Roblyer, M. D., & Marshall, J. (2002-2003). Predicting success of virtual high school distance learners: Preliminary results from an educational success prediction instrument (ESPRI). *Journal of Research on Technology in Education, 35* (2), 241-255.

Roblyer, M.D., Freeman, J., Stabler, M., & Schneidmiller, J. (2007). *External evaluation of the Alabama ACCESS Initiative: Phase 3 report.* Eugene, OR: International Society for Technology in Education.

Rouse, K. (2005, January 26). State's cyberschool students held back at higher rate. *Denver Post*, pp. A1, A10.

Russell, T. (2001). *The no significant differences phenomenon.* Littleton, Colorado: IDECC.

Santovec, M. (2004). Virtual learning communities lead to 80 percent retention at WGL. *Distance Education Report, 8*(8), 4.

Schrum, L., & Hong, S. (2002). Dimension and strategies for online success: Voices from experienced educators. *Journal of Asynchronous Learning Networks, 6*(1), 57-61.

Setzer, J., Lewis, L., & Greene, B. (2005). Distance education courses for public elementary and *secondary school students: 2002-03. (NCES No. 2005-010).* Washington, DC: National Center for Educational Statistics.

Slykhuis, D., & Park, J. (2006). Correlates of achievement with online and classroom-based MBL physics activities. *Journal of Computers in Mathematics and Science Teaching, 25*(2), 147-163.

Smith, P., & Dillon, C. (1999). Comparing distance learning and classroom learning: Conceptual considerations. *American Journal of Distance Education, 13*(2), 6-23.

State of Colorado. (2006, November). *Report of the state auditor: Online education performance audit.* Denver, Colorado: Office of the State Auditor.

Wang, A., & Newlin, M. (2000). Characteristics of students who enroll and succeed in web-based classes. *Journal of Educational Psychology, 92*(1), 137-143.

Waschull, S. (2005). Predicting success in online psychology courses: Self-discipline and motivation. *Teaching of Psychology, 32*(3), 190-192.

Watson, J., & Ryan, J. (2006). *Keeping pace with K-12 online learning: A review of state-level policy and practices.* Evergreen, Colorado: Evergreen Associates.

Watson, J., & Ryan, J. (2007). *Keeping pace with K-12 online learning: A review of state-level policy and practices.* Available at:

http://www.nacol.org/docs/KeepingPace07-color.pdf

Weiner, C. 2003. Key ingredients to online learning: Adolescent students study in cyberspace—the nature of the study. International Journal on E-Learning, 2 (3): 44-50.

Whipp, J., & Chiarelli. S. (2004). Self-regulation in a Web-based course: A case study. *Educational Technology Research & Development*, *52*(4), 5-22.

Willging, P., & Johnson, S. (2004). Factors that influence students' decisions to dropout of online courses. *Journal of Asynchronous Learning Networks*, *8*(4), 23-31.

Wojciechowski, A., & Palmer, L. (2005). Individual student characteristics: Can any be predictors of success in online classes? *Online Journal of Distance Learning Administration*, *8(*2). Available at: http://www.westga.edu/~distance/ojdla/summer82/wojciechowski82.htm

Wolcott, L. (1996). Distant, but not distanced. A learner-centered approach to distance education. *Techtrends, 41*(4), 23-27.

Zandberg, I., & Lewis, L. (2008). *Technology-based distance education courses for public elementary and secondary school students: 2002–03 and 2004–05* (NCES 2008–008). U. S. Department of Education. Washington, DC: Institute for Education Sciences, National Center for Education Statistics.

Zucker, A., & Kozma, R. (2003). *The virtual high school: Teaching generation V.* New York: Teachers College Press.

Table 1

Findings of Studies on Factors That Contribute to Success in Online Learning

Studies	**Student Characteristics**						**Course Environment**				
	LOC	**Tech. and online skills/ experience**	**Technology self-efficacy/ attitudes**	**Content area background**	**Other factors**	**GPA**	**Tech./ computer access**	**Tech. problems**	**Study environment**	**Support during course**	**Findings**
Dille & Mezack (1991)											Successful student more

	X				Age, marital status, hrs. completed						likely to be older, higher GPA, more completed hours, high internal LOC
Gibson & Graff (1992)					Learning styles	X					No learning style differences between completers, non-completers
Wang & Newlin (2000)	X				Learning styles, achieve-ment motivation, need for cognition						Successful online students had high internal LOC, need for cognition
Parker (2003)	X										Successful online students had high internal LOC
Waschull (2005)		X			Self-discipline, motivation, time commit-ment		X				Successful students had higher self-discipline, motivation
Maki & Maki (2002)		X									Students with higher skills in using multimedia content had higher achievement in web-based

											courses
DeTure (2004)			X		Field dependence/independence						Neither cognitive styles (indicated by field dependence/ independence) nor technology self-efficacy predicted success
Pillay, Irving, & McCrindle (2006)		X	X		Learning Preferences (online or traditional)						Model consisting of technical skills, technology self-efficacy, learning type preferences, and attitudes toward computers predicted success
Cheung & Kan (2002)				X	Attendance at tutorials, gender, previous achievement	X					Successful students tended to be female and those who attended tutorial sessions and had more background in the content

											area
Dupin-Bryant (2004)		X			Class rank	X					Students who persisted in online courses had higher GPA, class rank, Internet and technology experience
Bernard, Brauer, Abrami, & Surkes (2004)		X	X		Desire for interaction, self-direction and initiative	X					GPA best predictor of online success
Wojciechowski & Palmer (2005)						X				X	Attendance at orientation session and GPA predicted success in courses
Slykhuis & Park (2006)				X			X				Content area ability and experience were best predictors of success
Chyung (2001)										X	Various types of support during courses reduced dropout rate
Osborn (2001)											Students who had good study environment

			X						X		(place to complete online work) and computer confidence were less likely to drop out
Santovec (2004)										X	Virtual learning communities led to high retention rate
Willging & Johnson (2004)					Age	X		X			Wide variation in reasons for dropping out; higher GPA associated with failure, but not a strong predictor