Supporting Different Learning Styles in an Online Learning Environment:
Does it Really Matter in the Long Run?

Steven R. Terrell, Ed.D.
Graduate School of Computer and Information Science
Nova Southeastern University
Ft. Lauderdale , Florida 33314
954-262-2084
terrell@nova.edu

Introduction

Due to demands for educational programs that are time and place independent, distance education availability, course offerings, and enrollment increased rapidly during the 1990s. To illustrate this trend, the National Center for Education Statistics (2000) reported 91% of public four-year institutions and approximately 50% of all private institutions, representing a total of 1.6 million students, were currently offering, or planned to offer, distance education programs. Many of these programs are, or will be, delivered via an online learning environment.

Although retaining and graduating these students ultimately means success for an educational institution, most studies conducted thus far have focused on attrition at the course or semester level (e.g., Carr, 2000; Carr & Ledwith, 2000; Chyung, 2001; Diaz & Cartnal, 1999; Morgan & Tam, 1999; Neuhauser, 2002; Parker, 2003; Terrell, 2002; Terrell & Dringus, 1999). Since studies of this type may not help educators understand attrition at the program level, it is imperative that researchers examine attrition from a longitudinal perspective. This paper describes such an effort.

This study was conducted at a large, private, metropolitan university in southeastern Florida . As part of its distance education program, the university offers technology-oriented, limited-residency doctoral programs. Students are required to complete 40 hours (i.e., four semesters) of coursework prior to beginning work on the dissertation. Students typically enroll in ten hours of coursework each semester and are required to attend a weeklong session, or two-extended weekends, on campus during the semester. Upon completion of the coursework, students are allowed five years to complete the dissertation.

When students are not on campus, the class interacts using various synchronous and asynchronous tools. Although the faculty members may elect to use either or both of these communication modes, the majority of them choose an asynchronous approach. This preference (Passerini & Granger, 2000) reflects the trend in distance education programs.

Students in the programs come from varied backgrounds. Most are educators or information systems professionals interested in incorporating or expanding the use of technology in their given area of expertise. Although doctoral programs nationwide experience approximately a 50% attrition rate (Bowen & Rudenstein, 1992; National Research Council, 1996; Smallwood, 2004), students in the doctoral program investigated leave the program at a substantially higher rate (i.e. 62.4%).

Theoretical Framework

As noted by Rovai (2003), models for studying attrition in general have primarily been based "explain persistence and attrition through student-institution "fit" by looking at student, institutional and environmental variables and specific themes…" (p. 3). Two of the most prominent models, those of Tinto (1993) and Bean and Metzner (1985) state that characteristics such as age, gender, ethnicity and learning style should be considered while investigating attrition in these programs. While these models were developed to explain attrition in a traditional learning environment, Rovai indicates these factors should also be considered in an online learning environment. Unfortunately, "research attempts to establish a relationship between online graduate student retention and demographical characteristics has been inconclusive and contradictory" (Irizzary, 2002).

In an effort to further investigate this issue, this study examined the relationship between student age, gender, ethnicity, learning style and their effect on attrition from an online graduate program. The large number of learning theories upon which this investigation could be based mandated the identification and use of a theory that could be easily understood, measured and applied in such a setting. The work of Kolb (1984) was selected for this investigation.

According to Kolb, learners rely on four learning strategies: Concrete Experience, Abstract Conceptualization, Reflective Observation and Active Experimentation. The first of these strategies, Concrete Experience, emphasizes personal experience and feelings in a learning situation. Persons using this strategy are adaptable to change and are open-minded when approaching problems. The Abstract Conceptualization strategy calls for a reliance on the learner's ability to logically analyze ideas and systematically plan their approach to the task-at-hand. Learners in this, often called the thinking strategy, tend to refrain from decision-making until they have acquired an intellectual understanding of a given situation. Using the Reflective Observation strategy, a learner relies heavily on personal thoughts and feelings while placing special emphasis on patience, objectivity, careful judgment and the ability to understand ideas and problems from various points of view. The last strategy, Active Experimentation, involves learning taking an active form. Persons using this strategy are interested in what works and spend a great deal of time experimenting with changing or influencing situations.

The Kolb (1999) *Learning Style Inventory* (LSI) identifies a learner's preference for each of these four learning strategies. The resultant scores combine into two discrete, bipolar scales indicating a learner's preference for Active Experimentation versus Reflective Observation (i.e., the AERO scale) and Abstract Conceptualization versus Concrete Experience (i.e., the ACCE scale). The combination of the scores from the two scales identifies a learner's preferred style – Diverger, Converger, Assimilator or Accommodator.

Persons falling into the Converger and Assimilator types share a preference for high levels of Abstract Conceptualization. Convergers combine this preference with a need for Active Experimentation and prefer to learn via problem solving, deductive decision-making and the direct application of ideas and theories. Convergers have been described as somewhat unemotional with a preference for working alone. Assimilators, as the name suggests, prefer to combine Abstract Conceptualization with Reflective Observation and are good at taking in a wide range of information and reducing it to a more logical form. The Assimilator has a penchant for patient planning and problem definition and tends to prefer theoretical models and deductive reasoning; this leads to a greater interest in abstract concepts and ideas than interaction with other people.

Persons identified as Divergers or Accommodators rely heavily on Concrete Experience. Persons in the Accommodator category combine this strategy with a preference for Active Experimentation and are described as leaders who have the ability to carry out plans and get things done. Their tendency is to get involved quickly through a "hands on" or trial and error method of learning. Divergers prefer a combination of Concrete Experience and Reflective Observation and are characterized as open-minded and understanding with an ability to recognize problems and look at a learning situation from many points of view. They are often paralyzed by their inability to make a decision and, in many instances, prefer to observe rather than participate.

A given individual's occupation tends to reflect their personal learning style; examples of this are shown in Figure 1 (Kolb, 1999, p. 14). Because of the background of the student body (i.e., education and technology), it was hypothesized that the majority of the students would fall either into the Converger or Assimilator categories. It was further hypothesized, because of a learner's distinct talents and needs, learning style would be a significant predictor of success in such an environment.

Figure 1. Kolb Career Choices

<table>
<tr><td rowspan="3">Active Experimentation</td><td colspan="2">Concrete Experience</td><td rowspan="3">Reflective Observation</td></tr>
<tr><td>Accomodating
Management
Public Finance
Educational Administration
Marketing
Government
Human Resources</td><td>Diverging
Psychology
Nursing / Social Work
Public Policy
Theater
Literature / Journalism / Media
Design / Media</td></tr>
<tr><td>Converging
Engineering
Computer Science
Medical Technology
Farming / Forestry
Economics
Environmental Science</td><td>Assimilating
Physical Sciences
Biology
Math
Law
Teaching
Sociology/Theology</td></tr>
</table>

	Abstract Conceptualization		

Adapted from Kolb, (1984). *Experiential learning: experience as the source of learning and development.*
Author, 1984. Englewood Cliffs, NJ. Copyright 1984 by Prentice Hall.

Data Source and Methodology

The data for this longitudinal study were collected from 216 students who began a doctoral program between 1993 and 1998. Although students are allowed seven years to complete the program, all students involved in this study had either graduated or left the program by early 2003. During their coursework, students completed the Kolb *Learning Style Inventory* as part of a course in learning theory or research methodology. Students also provided information regarding their age, gender and ethnicity. These three variables will be included in the data analysis as research has shown their relevance when investigating attrition from a distance education program (Lantanich, Nonis & Hudson, 2001; Lim, 2001; Neuhauser, 2002; Sullivan, 2001).

Results and Conclusions

The sample of 216 students included 118 males (54.6%) and 98 females (45.4%) (Table 1). The difference in graduation rates between these two groups was not statistically significant ((1, N = 216) = .620, p = .259).

Table 1 - Graduation Rate by Gender

			Gender		
			Female	Male	Total
Graduate	No	Count	58	76	134
		% within Graduate	43.3%	56.7%	100.0%
	Yes	Count	40	42	82
		% within Graduate	48.8%	51.2%	100.0%
Total		Count	98	118	216
		% within Graduate	45.4%	54.6%	100.0%

Forty-eight (22.2%) of the participants were identified as members of a minority group (e.g., African-American, Asian-Pacific Islander, Hispanic, etc.). Many of the cell sizes for the individual groups were small (e.g., less than 10) therefore, in order to control for potential data analysis errors, all groups other than non-Hispanic whites were treated as a single entity (Table 2). Minority status did not significantly affect the overall graduation rate ((1, N = 216) = 1.181, p = .180).

			Minority	White	Total
Graduate	No	Count	33	101	134
		% within Graduate	24.6%	75.4%	100.0%
	Yes	Count	15	67	82
		% within Graduate	18.3%	81.7%	100.0%
Total		Count	48	168	216
		% within Graduate	22.2%	77.8%	100.0%

The average age of the students in the program was 43.37. Although the average age of students graduating from the program (i.e., 43.9) was slightly older than students leaving the program (i.e., 43.04), the difference was not significant (t (214)= .727, p = .468).

As hypothesized, the majority of students (167 or 77.3%) fell into either the Converger or the Assimilator category; of these, 37.1% (i.e., 62) graduated (Table 3). Of the 49 students falling into the Diverger or Accommodator categories, 20 (i.e., 40.8%) graduated. The overall comparison of graduation rate (38%) by learning style was not statistically significant ((3, N = 216) = 3.074, p = .380).

Table 3 - Graduation Rate by Learning Style

			Learning Style				
			Diverger	Accomodator	Converger	Assimilator	Total
Graduate	No	Count	7	22	52	53	134
		% within Graduate	5.2%	16.4%	38.8%	39.6%	100.0%
	Yes	Count	7	13	38	24	82
		% within Graduate	8.5%	15.9%	46.3%	29.3%	100.0%
Total		Count	14	35	90	77	216
		% within Graduate	6.5%	16.2%	41.7%	35.6%	100.0%

Since graduation status is dichotomous, the four independent variables (i.e., age, gender, ethnicity and learning style) were entered into a logistic regression equation to investigate their interaction in terms of predicting a given students probability of graduating. Table 4 shows the summary of the logistic regression model:

Table 4 - Logistic Regression Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	281.796	.023	.031

\

As can be seen, the large -2 Log likelihood indicates that the model is a poor predictor of attrition; a value approaching zero would indicate a good model fit. The Cox & Snell and Nagelkerke coefficients, both of which reflect the correlation between the predictor and criterion variables, support this observation. The weakness of the model results in a correct classification rate of only 62% (Table 5); this indicates the model is even less accurate than the 68% classification rate realized when no predictor variables are entered into the equation.

Observed			Graduate Yes	Graduate No	Percentage Correct
Step 1	Graduate	Yes	4	78	4.9
		No	4	130	97.0
	Overall Percentage				62.0

a. The cut value is .500

Discussion

Since the results were contrary to expectations, several things should be considered in an effort to understand them. These include the demographics of the student body, the motivation level of the students and the actual numeric scores on the LSI.

First, the typical student in the program is a working professional attempting to complete a degree in a limited residency doctoral program. For many it was their first experience in a distance education environment. Seventy-eight percent of the students were married; the average age was 42. Because these factors have been shown to affect educational achievement, researchers should be careful in attempting to generalize the results of this study to other populations.

Students in graduate school typically have higher levels of intrinsic motivation than students at other levels. Although not discussed in this paper, the students also completed the Nowicki-Strickland *Locus of Control Scale* (Nowicki & Duke, 1974) during their coursework . This instrument, designed to measure a student's perception of causality, correlates highly with instruments specifically designed to measure academic motivation. Scores on the instrument range from zero (i.e., a high internal locus of control) to 40 (i.e., a high external locus of control). The average score of 8.9 for participants in this study, representing a high internal locus of control (i.e., high intrinsic motivation), may indicate levels of intrinsic motivation high enough to allow students to compensate for their individual learning style preferences. The work of Lantanich et al. (2001) and Parker (2003) support this conjecture.

Consideration should also be given to the numeric values used to determine a particular students' category. Scores on the ACCE scale of the LSI range from 36 (i.e., high Abstract Conceptualization) to -21 (i.e., high Concrete Experience), while scores on the AERO scale range from 27 (i.e., high Active Experimentation) to -29 (i.e., high Reflective Observation). As was seen in Table 3, there was no significant difference in learning style between graduates and non-graduates. At the same time, Kolb indicates scores of six on the AERO scale and four on the ACCE scale indicate a mid-point on each of the scales; a learner scoring close to the mid-point can easily draw on skills and tactics preferred by each of the particular learning styles. The overall average score of the participants of 11.95 on the ACCE scale and 7.46 on the AERO scale may suggest that the average learner in the study group may have been able to balance their preferred learning style with the skills needed to succeed in the online learning environment.

Conclusions and Suggestions for Future Research

Educational institutions are quick to offer distance education programs as an alternative for students who, for myriad reasons, cannot attend a more traditional program. This trend is evidenced by the fact that over 80% of educational institutions in the United States offer some form of distance education. Unfortunately, attrition from these programs is reaching epidemic proportions and, if educational institutions are to fulfill their commitment to offer courses equivalent to their traditional counterparts, they must investigate ways to address the learning needs and styles of different types of learners.

First, in this case, the longitudinal attrition rate of graduate students was not affected by demographic and learning style variables under consideration; this may not hold true for learners at other levels (e.g., undergraduate, secondary and adult education). Given that, consideration should be given to investigating these same factors over extended periods of time in those types of programs.

Another consideration is the possibility of a change in preferred learning style over time. Students in this study completed the learning style inventory at the beginning of a seven-year program of study. No consideration was given to the possibility that a given student's learning preferences may change over time in order to compensate and adapt to an online learning environment. Longitudinal studies with learning style measured periodically should be considered.

Finally, developers and users of online learning environments at all institutions should consider *post-hoc* data collection and analysis. The use of interviews and questionnaires aimed at students' experiences in the program could yield data that might aid researchers in the identification of other personal or institutional factors that might be contributing to overall levels of attrition.

References

Bean, J. & Metzner, B. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research, 55,* 485-650.

Bowen, W.G. & Rudenstein, N.L. (1992). *In pursuit of the Ph.D.* Princeton , NJ : Princeton University Press.

Carr, R. & Ledwith, F. (2000). Helping disadvantaged students. *Teaching at a Distance, 18* , 77-85.

Carr, S. (2000, February 11). As distance education comes of age, the challenge is keeping the students. *The Chronicle of Higher Education* , p. A39-A41.

Chyung, S.Y. (2001). Systematic and systemic approaches to reducing attrition rates in online higher education. *The American Journal of Distance Education, 15* (3), 36-49.

Diaz, D., & Cartnal, R. (1999). Student's learning styles in two classes: Distance learning and equivalent on-campus. *College Teaching, 47* (4), 130-135.

Irizarry, R. (2002). Self-efficacy & motivation effects on online psychology student retention. *USDLA Journal, 16* (12). Retrieved May 19, 2004 , from http://www.usdla.org/html/journal/DEC02_Issue/article07.html .

Kolb, D. (1984). *Experiential learning: experience as the source of learning and development.* Englewood Cliffs, NJ: Prentice-Hall.

Kolb, D. (1999). *Learning-style inventory - version 3* . Boston : Hay/McBer Training Resources Group.

Lantanich, G., Nonis, S. & Hudson, G. (2001). A profile of today's distance learners: An investigation of demographic and individual difference variables of distance and non-distance learners. *Journal of Marketing in Higher Education, 11* (3), 1-16.

Lim, C. K. (2001). Computer self-efficacy, academic self-concept, and other predictors of satisfaction and future participation of adult distance learners. *American Journal of Distance Education, 15* (2), 41-51.

Moorhouse, D. (2000). *A Cross-Sectional Study of Graduation Rates by Major for the NSU 1994 Student Cohort.* (Rep. No. 00-07). Ft. Lauderdale , FL : Nova Southeastern University, Research and Planning.

Morgan, C.K & Tam, M. (1999). Unraveling the complexities of distance education student attrition. *Distance Education, 20* (1), 96-108.

National Center for Education Statistics. (2000). *Distance Learning in Higher Education Institutions.* (Rep. No. NCES 2000-053). Washington , DC : National Center for Education Statistics, Office of Educational Research and Improvement, U.S. Department of Education.

National Research Council. (1996). The path to the Ph.D.: *Measuring graduate attrition in the sciences and humanities* . Washington , D.C. : National Academy Press.

Neuhauser, C. (2002). Learning style and effectiveness of online and face-to-face instruction. *The American Journal of Distance Education, 16* (2), 99-113.

Nowicki, S. & Duke, M.P. (1974). A locus of control scale for noncollege as well as college adults. *Journal of Personality Assessment, 38* , 136-137.

Parker, A. (2003). Identifying predictors of academic persistence in distance education. *USDLA Journal, 17* (1). Retrieved May 19, 2004 , from http://www.usdla.org/html/journal/JAN03_Issue/article06.html .

Passerini, K. & Granger, M. (2000). A developmental model for distance learning using the Internet. *Computers & Education, 34* , 1-15.

Rovai, A.P. (2003). In search of higher persistence rates in distance education online programs. *The Internet and Higher Education, 6* (2003), 1-16.

Sullivan, P. (2001). Gender differences and the online classroom: Male and female college students evaluate their experiences. *Community College Journal of Research and Practice, 25* (10), 805-818.

Smallwood, S. (2004, January 16). Doctor dropout. *The Chronicle of Higher Education* , Retrieved March 18, 2005 , from http://chronicle.com/prm/weekly/v50/i19/19a01001.htm

Terrell, S. (2002). Learning style as a predictor of success in a limited residency doctoral program. *The Internet in Higher Education, 5* (4), 345-352.

Terrell, S., & Dringus, L. (1999). An investigation of the effect of learning style on student success in an online learning environment. *Journal of Educational Technology* Systems, *28* (3), 231-238.

Tinto, V. (1993). *Leaving college: rethinking the causes and cures of student attrition* . Chicago :

University of Chicago Press.

Online Journal of Distance Learning Administration, Volume VIII, Number II, Summer 2005
University of West Georgia, Distance Education Center
Back to the Online Journal of Distance Learning Administration Content