Technology Skill Development Among Education Majors

By Chad Sherman

ABSTRACT

This study sought to determine the influence that numerous variables have on the technology skill development of education majors. The study investigated how the participants' age, gender, race, ethnicity, level of comfort with technology, and learning style(s) correlated with their level of digital literacy. The results revealed that level of verbal-linguistic intelligence significantly correlated with the subjects' level of digital literacy, whereas the other seven multiple intelligence variables did not yield significant findings. Further statistical analysis demonstrated that each of the multiple intelligence variables (including level of verbal-linguistic intelligence) had a weak correlation with level of digital literacy when isolated from the other variables. Each one of the independent variables was found to be a poor predictor of the education majors' technology capabilities. Therefore, this article suggests that these variables (age, gender, level of prior technology use, etc.) should not be relied upon to predict a student's technology skills.

Key words: Digital literacy, Multiple intelligences, Educational technology, Learning styles

INTRODUCTION

This study sought to determine the influence that numerous variables had on the development of technology skills in education majors. According to some studies, college students display high levels of use of and comfort with computers and other digital tools (Smith, Salaway, & Caruso, 2009). Several scholars have tried to determine which variables most affect an individual's digital skills, but their findings have been inconclusive. Specifically, education majors are a substantial focus for analysis, because of the importance that has been placed on their digital competency (Banister & Vannatta, 2006). It has also been proposed that the digital skills of education majors are not sufficient for today's world.

PROBLEM STATEMENT

Banister and Vannatta (2006) acknowledged that many teacher candidates have deficiencies in their digital technology skills that should be addressed. Additionally, research is inconclusive about which demographics affect digital literacy (Barbour & Cooze, 2004; Dednam, 2009; Eshet, 2002; Eshet-Alkalai & Amichai-Hamburger, 2004; Eshet-Alkalai & Chajut, 2009; Hargittai, 2002; Hargittai, 2010; Smith et al., 2009). The literature, however, suggests that a student's learning style may correlate with that person's digital literacy. Several theorists have speculated that coordinating learning technologies with a student's learning style can provide a stronger educational experience (Gen, 2000; McCoog, 2007). Empirical evidence also suggests that there is a connection between a student's learning style and achievement in a technology-laden course (Barbour & Cooze, 2004.

Research Questions

The following research questions were developed:

- Does a preservice education major's verbal-linguistic intelligence significantly affect his or her score on a digital literacy assessment?
- Does a preservice education major's visual-spatial intelligence significantly affect his or her score on a digital literacy assessment?
- Does a preservice education major's logical-mathematical intelligence significantly affect his or her score on a digital literacy assessment?
- Does a preservice education major's musical-rhythmic intelligence significantly affect his or her score on a digital literacy assessment?
- Does a preservice education major's bodily-kinesthetic intelligence significantly affect his or her score on a digital literacy assessment?

- Does a preservice education major's interpersonal intelligence significantly affect his or her score on a digital literacy assessment?
- Does a preservice education major's intrapersonal intelligence significantly affect his or her score on a digital literacy assessment?
- Does a preservice education major's naturalistic intelligence significantly affect his or her score on a digital literacy assessment?
- To what degree does the interplay between the eight multiple intelligence learning styles predict preservice education majors' level of digital literacy?

Hypotheses

The alpha level for this study is $p = .05$. The following hypotheses were developed:

- A preservice education major's verbal-linguistic intelligence positively affects his or her score on a digital literacy assessment.
- A preservice education major's visual-spatial intelligence positively affects his or her score on a digital literacy assessment.
- A preservice education major's logical-mathematical intelligence positively affects his or her score on a digital literacy assessment.
- A preservice education major's musical intelligence does not significantly affect his or her score on a digital literacy assessment.
- A preservice education major's bodily-kinesthetic intelligence does not significantly affect his or her score on a digital literacy assessment.
- A preservice education major's interpersonal intelligence does not significantly affect his or her score on a digital literacy assessment.
- A preservice education major's intrapersonal intelligence does not significantly affect his or her score on a digital literacy assessment.
- A preservice education major's naturalistic intelligence does not significantly affect his or her score on a digital literacy assessment.
- The eight multiple intelligence learning styles predict preservice education majors' level of digital literacy.

Review of the Literature

Gardner's theory of multiple intelligences (1983) offered an improved method to describe intelligence and put a focus on individualized education. The theory was developed to focus on how a student prefers to learn--an approach not commonly seen in education until recent decades (Gardner, 2003; Teele, 2000).

Gardner theorized that each student has a unique set of intelligences to which they adapt their learning processes. Each student learns in an individual manner (Gardner, 1993a, 1999, 2003; Teele, 2000). Varying types of instruction are required to stimulate and encourage students to utilize their own unique learning styles. Gardner's theories have been applied mostly to educational psychology, but they also can be applied to digital literacy (Barbour & Cooze, 2004; Gen, 2000; McCoog, 2007; McCoog, 2010) and to education (Campbell, 1990). Gardner (1993b) also theorized that multiple intelligence theory could be combined with digital literacy. He argued that computers can be utilized to match individuals to a mode of instruction that is best suited to their intelligence. Gardner (1995) added that this combination forms the foundation for a great education. Other scholars have argued that digital technology can be used to great such a foundation (Gen, 2000; Grant, 1999; Leu, Leu, & Len, 1997; McCoog, 2007; Silver, Strong, & Perini, 2000).

Limited Effects of Several Demographics

Several demographics may correlate with an individual's digital literacy abilities. However, the literature in this area is inconclusive at best. Because the literature concentrates heavily on these demographics, they will be briefly discussed.

Age

Eshet's (2002) qualitative study suggested that a relationship exists between age and digital literacy. Eshet-Alkalai and Amichai-Hamburger (2004) found that adults scored significantly

lower than other age groups. Eshet-Alkalai and Chajut (2009) conducted a follow-up study and found similar results.

Other researchers have identified mitigating factors. For example, Hargittai (2002) argued that such findings were likely due to their varied levels of comfort with technology. Likewise, van Deursen and van Dijk (2008) similarly suggested that extraneous variables likely were more accountable for variations in digital literacy than age. Other researchers have failed entirely to find a correlation between age and digital literacy (Hargittai, 2012; Koroghlanian & Brinkerhoff, 2008).

Gender

Shashaani (1997) identified significant differences between the attitudes of males and females regarding computers. However, the study specifies that previous experience is likely the source of the difference. Similarly, Comber, Colley, Hargreaves, and Dorn (1997) proposed that males have more confidence when using computers. When previous was controlled for, the researchers found no statistically significant differences.

It has been suggested that men and women also differ in their usage of specific computer technologies. Men are more intensive Internet users than women (Bimber, 2000) and use the Internet more frequently (Jones, Johnson-Yale, Millermaier, & Pérez, 2009). Others (Jackson, Yong, Kolenic, Fitzgerald, Harold, & Von Eye, 2008) have suggested that men and women significantly differ in the intensity and nature of their technology use.

Gender also may predict how an individual applies technology to his or her life. Van Braak, Tondeur, and Valcke (2004) found that male teachers integrate computers into their classrooms more often. Karsten and Schmidt (2008) discovered that female business students scored significantly lower on a measure of computer self-efficacy. Koroghlanian and Brinkerhoff (2008) found significant differences indicating that males have higher digital literacy than do females. Males also scored significantly higher on an assessment of several digital skills (Butler, Ryan, & Chao, 2005).

Socioeconomic Status

Studies have shown that socioeconomic status correlates with an individual's own perception of digital literacy capabilities (Hargittai, 2010). Similarly, Jackson et al. (2008) found that students' socioeconomic characteristics were an accurate judge of the intensity and nature of the students' technology usage.

Race and Ethnicity

According to Hargittai (2010), race affects individuals' self-perceptions of their digital skills. Specifically, African American and Hispanic students rated their digital knowledge more poorly than did Caucasian students. Jackson et al. (2008) found similar differences between African American and Caucasian children in the intensity and nature of their technology use.

Several studies have suggested that race is not an accurate predictor of digital literacy. For example, Jackson et al. (2008) concluded that prior experience with technology is a better predictor. Further, Jackson, Yong, Witt, Fitzgerald, von Eye, and Harold, (2009) failed to identify a significant difference between participants of different races. Also, Jones et al. (2009) failed to find a significant difference between participants of different races.

Technology Experience

Researchers van Deursen and van Dijk (2008) found experience to be a significant predictor of an individual's digital technology capabilities. Both the number of years with technology access and the number of hours spent per week with technology positively relate to an individual's digital skills (Hargittai, 2010). Even students who had taken one advanced computer class did better on several technology assessments (Koroghlanian & Brinkerhoff, 2007). Similarly, the level of integration of technology in high school education has an effect on how much an individual will value technology later (Banister & Ross, 2006). However, some scholars counterpropose that previous experience with computers does not affect a student's digital literacy (Comber et al., 1997).

Education

Some scholars have stated that level and quality of education has an impact on digital literacy. Teske and Etheridge (2010) argued that honor students are more digitally literate than non-honors students. Although, van Deursen and van Dijk (2008) only found education to be

a significant predictor of the time it takes to complete digital tasks. Bonfadelli (2002) contradicted the previous studies and claimed that education level cannot be used to predict digital literacy, but it can be used to predict how an individual may use it.

Education Majors' Multiple Intelligences and Digital Literacy

The digital and technological skills of teacher candidates vary greatly (Banister & Ross, 2006). For these teacher candidates to effectively integrate technology into their future classrooms, they must first acquire the skills themselves. Martinez (2010) similarly posited that education majors must learn the technology skills before they can teach it to others. Teaching cannot be as effective without successful implementation of information and communication technology (Ertmer & Ottenbreit-Leftwich, 2010).

Application of Multiple Intelligences to Digital Literacy

Digital technologies can effectively be used to teach students who have an assortment of intelligences. Gardner (1993b) commended the ability of technology to help students meet and surpass educational goals. He advised that students' primary intelligences should be matched with appropriate technology. This combination is likely to improve the students' learning (Gardner, 1995). Further, several scholars have listed specific digital tools and lessons that can advance the digital classroom experience (Gen, 2000; Grant, 1999; Leu et al., 1997; McCoog, 2007; Silver et al., 2000). Although empirical evidence in the literature is limited, it may be possible to predict a student's score on such digital assessments by knowing his or her dominant intelligence(s). For example, it was found that musical and verbal-linguistic learners performed more poorly in a class delivered online (Barbour & Cooze, 2004). Other scholars also have established that learning improves when the teacher matches the selected digital technologies with the students' intelligence profiles (Gen, 2000; McCoog, 2007). Overall, technology in the classroom is vital because it has an excellent capacity to engage and challenge students (Grant, 1999).

MATERIALS AND METHODS

The study sought to examine the relationship between preservice education majors' multiple intelligence learning styles and their levels of digital literacy. A quantitative survey was employed for this study. The independent variable was the subjects' scores on a multiple intelligences assessment. The dependent variable was the subjects' scores on a digital literacy assessment. The alpha level for this study is $p = .05$.

Procedure

All participants were assigned a username and password for admittance to the digital literacy assessment. Students could not be identified by their usernames. All participants were enrolled in a digital technology course. Their instructors were not informed about which responses were made by any particular student.

Subjects in this study completed three stages of data collection. First, data was collected on the students' demographics. This step was administered to determine the heterogeneity of the sample. This step used a descriptive survey. This survey was administered online through Qualtrics.

Second, the students' learning styles were measured using an assessment developed by Gürcüm (2010). This survey was also administered online through Qualtrics.

Third, each participant's digital literacy was assessed through the Instant Digital Competence Assessment developed by Calvani, Cartelli, Fini, & Ranieri (2009). It was administered online through the Instant Digital Competence Assessment website. Students were required to provide their anonymous usernames for each step so their responses could be matched.

Setting

This study was conducted at Indiana University of Pennsylvania where education majors are required to meet the International Society for Technology in Education's NETS standards. The study was administered online.

Population and Sample

All participants (n =101) included in the study were enrolled in one of ten digital instructional technology courses. Participation in the study was voluntary. Students were not included in the sample if they had previously been enrolled in one of the courses. This was done to control for prior knowledge and to minimize threats to external validity. The survey was administered during the first two weeks of the semester.

Instrumentation

A seven-item descriptive questionnaire was used to describe the sample. The assessment measured several variables recognized in the literature review: age, gender, socioeconomic status, prior technology experience, education level, and race.

Each subject's multiple intelligences learning style was measured using a 142-item multiple intelligences inventory designed by Gürcüm (2010). The inventory was comprised of Likert-type questions. The instrument's coefficient of reliability is acceptable (.943).

The participants' digital literacy was measured through the Instant Digital Competence Assessment (iDCA) developed by Calvani et al. (2009). The iDCA was designed to match the authors' model of digital competence (Calvani et al., 2009).

The assessment was found to be valid by a panel of experts (Calvani et al., 2009). The instrument was found to have an acceptable level of reliability (Cronbach's alpha = 0.79).

RESULTS

The data was coded into an electronic spreadsheet. All data was merged into one electronic spreadsheet. The data was ordered by each participant's numeric username.
Several descriptive statistics were analyzed to describe the sample. This step examined the heterogeneity of the sample. Next, a Pearson's r correlation cross-tabulation was used to determine whether any of the eight multiple intelligence learning style categories correlated with digital literacy. Lastly, a multiple linear regression test was used to determine the degree to which the interplay between the eight multiple intelligence learning style variables predicted the score on the digital literacy assessment.

Description of the Sample

Several statistics were analyzed to describe the sample. The examined demographics were identified in the literature review: age, gender, socioeconomic status, prior technology experience, education level, and race. The statistics indicate that the sample is relatively homogenous.

Age

A majority of the students in the sample were between the ages of 18 and 20 (88.1%). Participants aged 21 years or older constituted 11.9% of the sample. No participants were under the age of 18.

These results were anticipated because most education majors at the host university are required to enroll in the digital instructional technology course during their freshman or sophomore years.

Gender

Most students included in the sample for this study were female (70.3%). Less than one third (29.7%) of participants were male.

Parental Education

A majority of students (77.2%) indicated that their parents' education levels included at least some college. Less than one quarter of the students (22.8%) stated that their parents had a high school degree or less.

According to Sewell (1971), this percentage of college-educated parents indicates that most of the participants in this study had a relatively comfortable socioeconomic status. Therefore, the students included in the sample for this study should have been capable of receiving an acceptable mark on a digital literacy assessment (Hargittai, 2010).

Technology Experience

Most participants (94%) signified that they had familiarity with digital technologies for at least 6 years, and a large proportion stated that they had at least 10 years of experience.

The students had a significant amount of experience using digital technologies. This is comparable to the findings of Smith et al. (2009; however, it does not indicate that the students are also digitally literate. Having access to digital technology does not denote acceptable digital literacy (Hargittai, 2010).

Education Level
A large majority (96%) of the participants held a high school degree and had taken at least one college course. A small proportion (4%) of this sample had previously earned a college degree.

Race/Ethnicity
The majority of respondents (94.1%) identified themselves as White/Caucasian. Small proportions identified themselves as Black/African American (4%), Hispanic (1%), and Asian (1%).

These distributions are not representative of the university. The ratio of White/Caucasian students to minority students is not as exaggerated (Crimson Snapshot, 2011). Because this was a volunteer sample, the results were generalized to a larger population.

The Multiple Intelligence Learning Styles' Relationship To Level Of Digital Literacy
A Pearson *r* correlation cross-tabulation statistic was used to determine if the eight learning styles correlated with the students' digital literacy capabilities. A significant, positive correlation (.188) was found between the participants' verbal-linguistic learning style and their level of digital literacy at the $p = .05$ level. However, the correlation is noticeably weak. The significance (.030) is similarly weak. However, because a positive and significant correlation between the two variables exists, the hypothesis is supported. Correlational analyses failed to find any level of significance between logical-mathematical, visual-spatial, musical-rhythmic, bodily-kinesthetic, interpersonal, intrapersonal, and naturalistic learning style and digital literacy. The hypotheses are, therefore, not supported.

The Multiple Intelligences Learning Styles as Predictors of Digital Literacy Capabilities
A multiple regression analysis was also conducted. The eight multiple intelligence learning styles were used as the independent variables. The students' scores on the digital literacy assessment were used as the dependent variable. This analysis sought to determine how well the multiple intelligence learning styles work together to predict an individual's digital literacy.

The multiple intelligences model as a whole was a poor predictor of the participants' digital literacy ($r = .255$). The low *r*-squared value (.065) similarly supported this finding.

The multiple regression results did not identify any significant correlations between each of the eight multiple intelligences and the digital literacy variable. The strongest coefficient was found with the verbal-linguistic variable ($b = .062$, $p = .019$). This was expected, given the significant finding of the Pearson *r* analysis. The multiple regression analysis minimizes this finding.

CONCLUSION

This section will summarize the outcomes of the previous chapter and include a discussion of the relationship between the eight multiple intelligence variables and level of digital literacy.

Verbal-Linguistic Intelligence

Verbal-linguistic intelligence was found to have a significant, positive correlation to the education majors' digital literacy. This contradicts the findings of Barbour and Cooze (2004), which indicated that verbal-linguistic learners perform more poorly in a digital environment.

Further analysis, however, determined that verbal-linguistic intelligence did not have a significant correlation with digital literacy. This does not support the theories of researchers who theorized that verbal-linguistic learners might perform well in digital environments (Gen, 2000; Jackson et al., 2009; Leu et al., 1997). This finding does not conflict with Gardner's (1983, 1995) notion that a learner's verbal-linguistic learning style should correspond with his/her score on a verbal-linguistic assessment.

The Remaining Learning Styles

The remaining multiple intelligence learning style variables did not significantly correlate with level of digital literacy. This finding contradicts the theoretical base of this study, which was developed from Gen (2000), Grant (1999), Leu et al. (1997), McCoog (2007), and Silver et al. (2000). When the eight independent variables were analyzed as a whole, none were found to have a significant correlation with digital literacy. These eight multiple intelligence variables are not accurate predictors of participants' level of digital literacy. A student's learning style should not be used to predict his/her score on a generalized digital literacy assessment.

Multiple Intelligences as a Model for Predicting Level of Digital Literacy

Gardner's (1983) claim that individualized instruction should be matched with similarly individualized assessment strategies is the foundation of the multiple intelligences theory. The use of a general (rather than individualized) assessment in this study also may explain why the learners' scores varied so greatly—a finding that is reinforced by the work of Banister and Vanatta (2006). Therefore, it is recommended that future studies in this area utilize an individualized assessment plan.

The Other Variables

Several other independent variables similarly were found to be poor predictors of the subjects' technology capabilities. Some of the findings (e.g., gender) support the findings of other notable studies. However, some findings (e.g., level of prior technology use) contradict findings that state that people with higher technology experience should score higher on an assessment of their technology skills. This was not seen in this study, however. Therefore, it cannot be suggested that any of the independent variables analyzed for this study can be claimed as accurate predictors of an education major's technology skills.

Chad Sherman, Ph.D. is an Assistant Professor of Communication at Waynesburg University, Pennsylvania.

REFERENCES

Banister S., & Ross C. (2006). From high school to college: How prepared are teacher candidates for technology integration? *Journal of Computing in Teacher Education*, *22*(2), 75-80.

Banister S., & Vannatta, R. (2006). Beginning with a baseline: Insuring productive technology integration in teacher education. *Journal of Technology and Teacher Education*, *14*(1), 209-235

Barbour, M., & Cooze, M. (2004). *Learning styles and Web-based design for secondary students*. Paper presented at the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education, Chesapeake, VA.

Bimber, B. (2000). Measuring the gender gap on the Internet. *Social Science Quarterly*, *81*(3), 868-876.

Bonfadelli, H. (2002). The Internet and knowledge gap: A theoretical and empirical investigation. *European Journal of Communication*, *17*(1), 65-84.

Butler, T., Ryan, P., & Chao, T. (2005). Gender and technology in the liberal arts: Aptitudes, attitudes, and skills acquisition. *Journal of Information Technology Education*, *4*, 347-362.

Campbell, B. (1990). The research results of a multiple intelligences classroom. *New Horizons for Learning's On the Beam, 11*(1), 7.

Calvani, A., Cartelli, A., Fini, A., & Ranieri, M. (2009). Models and instruments for assessing digital competence at school. *Journal of e-Learning and Knowledge Society, 4*(3), 183-193.

Comber, C., Colley, A., Hargreaves, D. J., & Dorn, L. (1997). The effects of age, gender and computer experience upon computer attitudes. *Educational Research, 39*(2), 123-133.

Crimson Snapshot (2011). *General format*. Retrieved from http://www.iup.edu/snapshot

Dednam, E. (2009). *Away with computer literacy modules at universities, or not?* Paper presented at the 2009 Annual Conference of the Southern African Computer Lecturers' Association, Eastern Cape, South Africa.

Ertmer, P., & Ottenbreit-Leftwich, A. (2010). Teacher technology change: How knowledge, confidence, beliefs, and culture intersect. *Journal of Research on Technology in Education, 42*(3), 255–284.

Eshet, Y. (2002). Digital literacy: A new terminology framework and its application to the design of meaningful technology-based learning environments. In P. Barker & S. Rebelsky (Eds.), *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications* (pp. 493-498). Chesapeake, VA: Association for the Advancement of Computing in Education.

Eshet-Alkalai, Y. (2004). Digital literacy: A conceptual framework for survival skills in the digital era. *Journal of Educational Multimedia and Hypermedia, 13*(1), 93-107.

Eshet-Alkali, Y., & Amichai-Hamburger, Y. (2004). Experiments in digital literacy. *CyberPsychology & Behavior, 7*(4), 421-429.

Eshet-Alkalai, Y., & Chajut, E. (2009). Changes over time in digital literacy. *CyberPsychology & Behavior, 12*(6), 713-715.

Gardner, H. (1983). *Frames of mind: The theory of multiple intelligences*. New York: Basic Books.

Gardner, H. (1993a). *Frames of mind: The theory of multiple intelligences (2nd ed.)*. New York: Basic Books.

Gardner, H. (1993b). *The unschooled mind: How children think and how schools should teach*. New York: Basic Books.

Gardner, H. (1995). Reflections on multiple intelligences: Myths and messages. *Phi Delta Kappan, 77*(3), 200-203, 206-209.

Gardner, H. (2003). *Multiple intelligences after twenty years*. Cambridge, MA: American Educational Research Association.

Gen, R. (2000). Technology and multiple intelligences. *ED at a Distance, 15*(5), 4-9.

Grant, C. (1999). *Proceedings of the National Association for Multicultural Education*. Mahwah, NJ: Lawrence Erlbaum Associates.

Gürcüm, B. (2010). Determining the level of success by multiple intelligences theory for fashion design education. *e-Journal of New World Sciences Academy, (5)*2, 66.

Hargittai, E. (2002). Second-level digital divide: Differences in people's online skills. *First Monday, 7*(4). Retrieved from http://www.firstmonday.org/issues/issue7_4/hargittai/

Hargittai, E. (2010). Digital na(t)ives? Variation in Internet skills and uses among members of the "Net generation." *Sociological Inquiry, 80*(1), 92-113.

Jackson, L. A., Yong, Z., Kolenic, A., III, Fitzgerald, H. E., Harold, R., & Von Eye, A. (2008). Race, gender, and information technology use: The new digital divide. *CyberPsychology & Behavior, 11*(4), 437-442.

Jackson, L. A., Yong, Z., Witt, E. A., Fitzgerald, H. E., von Eye, A., & Harold, R. (2009). Self-concept, self-esteem, gender, race, and information technology use. *CyberPsychology & Behavior, 12*(4), 437-40.

Jones, S., Johnson-Yale, C., Millermaier, S., & Pérez, F. (2009). U.S. college students' Internet use: Race, gender and digital divides. *Journal of Computer-Mediated Communication, 14*(2), 244-264.

Karsten, R., & Schmidt, D. (2008). Business student computer self-efficacy: Ten years later. *Journal of Information Systems Education, 19*(4), 445-454.

Koroghlanian, C., & Brinkerhoff, J. (2007). Online students' technology skills and attitudes toward online instruction. *Journal of Educational Technology Systems, 36*(2), 219-244.

Leu, D., Leu, D., & Len, K. (1997). *Teaching with the Internet: Lessons from the classroom*. Norwood, MA: Christopher-Gordon Publishers, Inc.

Martinez, M. (2010). Teacher education can't ignore technology. *Phi Delta Kappan, 91*(10), 74-75.

McCoog, I. (2007). Integrated instruction: Multiple intelligences and technology. *The Clearing House: A Journal of Educational Strategies, Issues, and Ideas, 81*(1), 25-28.

McCoog, I. (2010). The existential learner. *The Clearing House: A Journal of Educational Strategies, Issues, and Ideas, 83*(4), 126-128.

Sewell, William H. 1971. "Inequality of Opportunity for Higher Education." *American Sociological Review, 36*, 793-809.

Shashaani, L. (1997). Gender differences in computer attitudes and use among college students. *Journal of Educational Computing Research, 16*(1), 37–51.

Silver, H., Strong, R., & Perini, M. (2000). *So each may learn: Integrating learning styles and multiple intelligences*. Alexandria, VA: Association for Supervision and Curriculum Development.

Smith, S., Salaway, G., & Caruso, J. (2009). The ECAR study of undergraduate students and information technology, 2009. Retrieved from http://net.educause.edu/ir/library/pdf/ers0906/rs/ERS0906w.pdf

Teele, S. (2000). *Rainbows of intelligence: Exploring how students learn*. Thousand Oaks, CA: Corwin Press.

Teske, B., & Etheridge, B. (2010). Information and communication technology literacy among first-year honors and non-honors students: An assessment. *Journal of the National Collegiate Honors Council, 11*, 83-109.

Van Braak, J., Tondeur, J., & Valcke, M. (2004). Explaining different types of computer use among primary school teachers. *European Journal of Psychology of Education, 14*(4), 407-422.

van Deursen, A., & van Dijk, J. (2008, May). *Measuring digital skills. Performance tests of operational, formal, information and strategic Internet skills among the Dutch population*. Paper presented at the ICA Conference, Montreal.