TECHNOLOGY KNOWLEDGE SELF-ASSESSMENT AND PRE-TEST PERFORMANCE AMONG DIGITAL NATIVES

Keith R. Nelms, Professor

Walker School of Business Piedmont College Demorest, Georgia

ABSTRACT

According to education pundits, traditional-age college students are "digital natives" inherently savvy in digital technology due to their constant exposure to technology from an early age. This widely held meme is at odds with observation in the college classroom. In this research, college students in an introductory information technology course are surveyed prior to instruction regarding perceptions of their own technological expertise in hardware, software, networking, research, computer graphics, computer security, Microsoft Word, Microsoft Excel, and Microsoft Power-Point. Students are then given pre-tests to assess their expertise in these topics based on course standards. Data from the survey and the pre-tests are analyzed. Although students self-assess slightly greater expertise in areas in which they actively use computers (Windows, Word, PowerPoint, and Research), they generally do not claim technological expertise. This lack of expertise is confirmed in pre-tests scores. Data analysis provides no support for the "digital native" meme.

INTRODUCTION

Among the several monikers attached to the current generation of traditional-age students, "digital natives" might be the most misleading. Coined by educational futurists in the early 2000s, the digital native meme suggests individuals born after a certain date are naturally fluent with modern information technologies (Prensky, 2001). Just as small children learn language through constant exposure in their preschool years, digital natives supposedly became fluent in computing and telecommunications technologies because these digital technologies were ubiquitous in their childhood environment. Thus, these digital natives do not need to be taught about technology—they "just do it." In contrast, older generations are not so fortunate. They are "digital immigrants" who are always awkward in the digital environment, never quite comfortable in the foreign land of technology in which they did not grow-up.

The "digital native" meme has obvious logical flaws (technology creators were digital immigrants, for example). Even so, this meme has proven quite popular in both the educational environment and in popular culture. In some colleges, it has even guided curriculum decisions. However, research and deeper investigation does not support its veracity (Bennet, Maton, & Kerin, 2008; Brown & Czerniewicz, 2010; Brumberger, 2011; Helsper & Eynon, 2010; Margaryan, Littlejohn, & Vojt, 2011; Ng, 2012; O'Neil, 2014).

Despite being repeatedly discredited, the digital native myth persists. But what do the "digital natives" think? Having grown-up surrounded by technology and having been told their entire lifetimes (by some) they are knowledgeable about technology, do they consider themselves technologically adept? How well do they perform when confronted with questions or tasks involving technology? Students' self-assessment of their own expertise influences their attitude and perceptions about the need to study in courses involving technology.

BACKGROUND

The National Research Council's Fluency in Technology model (National Research Council, 1999) provides the framework for the introductory technology course in which this research is conducted. The NRC states fluency in information technology is composed of three components – contemporary skills (accomplish common tasks using today's technology), foundation concepts (understand basic principles and ideas underlying technology), and intellectual abilities (use technology to address complex problems). Course assignments and testing are designed to develop technological fluency among students.

Course Technology's SAM Office 2010 training and testing system is used to teach contemporary skills in Microsoft Word, Excel, and PowerPoint. SAM's training modules provide a conceptual framework for each skill then demonstrates the skill online. Students are then required

to perform the skill for SAM to provide graded credit. to mark the line associated with each topic based on as-Instruction is at the level of Course Technology's New Perspectives series introductory textbook (Shaffer, et al., 2011) with a handful of advanced topics in Word and Excel specifically requested by upper division course instruc-

Lecture, classroom activities, readings, and digital videos are used to teach concepts about hardware, software, networking, research, computer graphics, security as well as word processing, spreadsheets, and presentations. Content in these topics is based on Internet & Core Computing Certification Global Standard 4 (CertiPort, n.d.) at the level of a widely used college technology literacy textbook (Parsons & Oja, 2011) and augmented based on information literacy guidelines from the American Library Association (n.d.).

SAM 2010 online tests are used to evaluate skills mastery. SAM simulates a screen from Word, Excel, or PowerPoint and requires students to complete a defined task (such as create a new style in Word or edit a pivot table in Excel). SAM allows up to three attempts by the student before rendering a pass/fail assessment on that individual task. Skills tests in this course contain approximately 50 tasks.

Concept tests are conducted using the Moodle learning management system. Questions are primarily multiplechoice with some true-false, matching, and short answer. For each concept to be tested, Moodle maintains multiple equivalent questions in a test bank. Tests are generated individually for each student by assembling randomly selected test bank questions. Thus, each student has a different but equivalent test.

The instructor administers skills and concepts pre-tests prior to instruction in this course. The SAM skills pretests are the same tests administered later in the semester for course credit. The concepts pre-tests are modified versions of the course final exam (questions about course-specific activities found in the final exam are removed from the pre-tests).

METHODOLOGY

This research study was conducted in three freshman-level information technology courses in Fall 2013. There were 41 students in the study. Most students were first semester freshman of traditional age and were graduates of suburban high schools. A few students were sophomore or juniors transfers. Students not in their late teens were in their early-to-mid twenties.

In the first week of the course, the author administered a survey asking students to rate their perceived expertise in course topics (see Figure 1). Students were instructed

sessment of his or her existing knowledge (Aiken, 1996). This graphical rating scale was later measured and student responses were recoded to a Ø-to-100 scale.

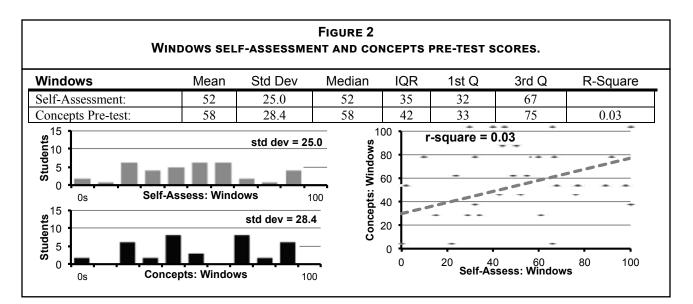
Prior to course instruction, students completed the concepts pre-test and the SAM 2010 skills pre-tests for Microsoft Word, Microsoft Excel, and Microsoft PowerPoint.

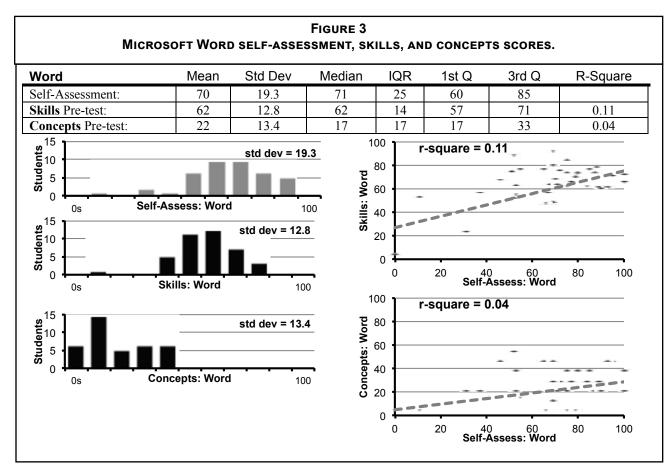
RESULTS

Figures 2 through 11 provide the mean, standard deviation, median, interquartile range, first quartile, and third quartile for each self-assessment and pre-test distribution. The r² coefficient of determination between each self-assessment and its associated pre-test is provided. Data from each distribution are binned and displayed in histograms. A scatterplot displays the relationship between each student's self-assessment and pre-test score. Note that Microsoft Word, Microsoft Excel, and Microsoft PowerPoint have both skills pre-tests and concepts pre-tests and thus have two sets of pre-test distributions and graphs.

At the aggregate level, students assess a modest level of expertise in using the Microsoft Windows operating system.

FIGURE 1 SELF-ASSESSMENT SURVEY INSTRUMENT. TM 200 Computer Skills Self-Assessment In each of the categories listed below, place a single vertical mark on the associated line Interest in TM 200 course content Microsoft Word Microsoft Excel Microsoft PowerPoint Microsoft Access Computer Hardware Computer Software





The means, standard deviations, and interquartile ranges of self-assessment and concept test performance appear reasonably consistent. At the individual student level, however, there is little correlation between self-assessed knowledge and performance in the concepts pre-test.

At the aggregate level, students profess greater self-assessed expertise in Microsoft Word than any other topic. The aggregate performance on skills testing is only slightly lower $(\mu=62)$ than the professed expertise $(\mu=70)$. However, the aggregate performance on the concepts pre-text is much

100 101 Spring 2015 (Volume 11 Issue 1) Journal of Learning in Higher Education

lower (μ =22). At the individual student level, the correlation between self-assessed knowledge and skills performance is slight but correlation between self-assessment and the concepts pre-test score is practically non-existent.

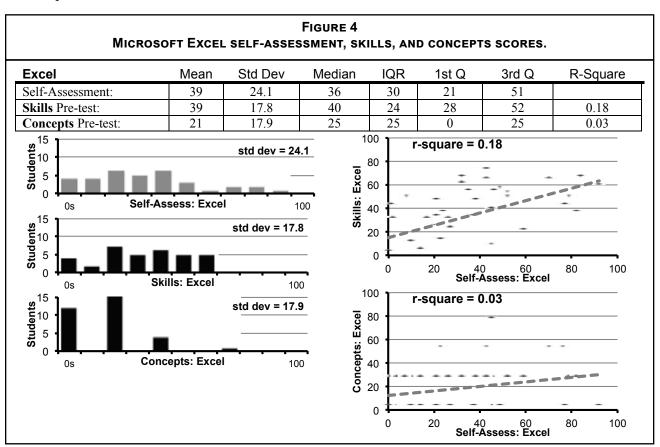
At the aggregate level, students did not profess as much expertise in Excel as they did in Word and PowerPoint. The aggregate self-assessment distribution was very consistent with aggregate performance on the skills pre-test (both with μ =39). Aggregate performance on the concepts test was very poor. At the individual level, the correlation between self-assessed knowledge and skills performance is the second highest in this study (r^2 =0.18). Correlation between self-assessment and the concepts pre-test score is practically non-existent.

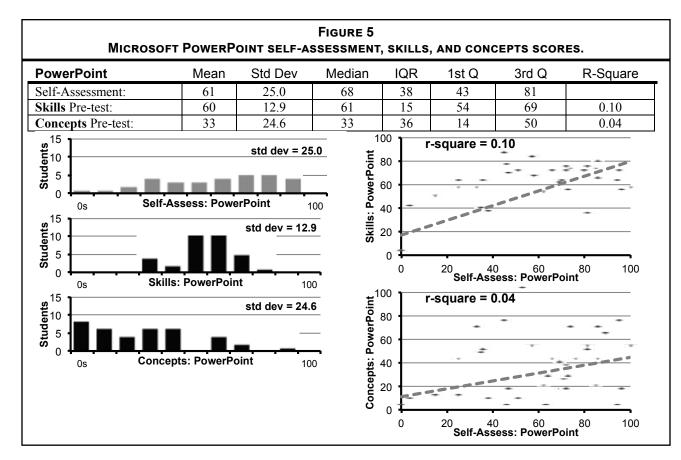
At the aggregate level, student self-assessed expertise in PowerPoint is second only to their perceived expertise in Microsoft Word. The means of the self-assessment (μ =61) and skills pre-test (μ =60) are consistent, though the standard deviation and interquartile range for the skills test are much smaller. While the performance on the concepts pre-test is again much poorer than in the skills pre-test, scores for the PowerPoint concepts test are noticeably higher than those in Word or Excel. At the individual student level, correlation between self-assessment and performance is poor.

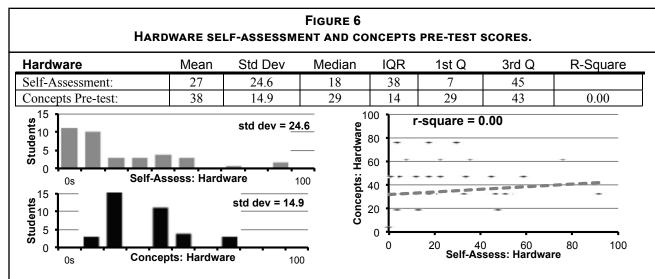
Aggregate self-assessment data indicates students have little confidence in their hardware knowledge. Performance in the concepts pre-test was actually slightly better than aggregate self-assessment – likely due to the multiple-choice nature of the pre-test. The bulk of the students scored at the level of "guessing" on hardware questions (approximately 25%). At the individual student level, the correlation between self-assessed knowledge and test performance is zero.

Aggregate self-assessment for software is very similar to the self-assessment for hardware above – students profess very little expertise. Performance on the software concepts pre-test was better than for the hardware pre-test and actually better than the self-assessment (though this is likely an artifact of a multiple-choice testing environment). At the individual level, correlation between self-assessment and concepts test performance ($r^2=\emptyset.19$) is higher than any other correlation in the study.

Despite seemingly constant use of networking and telecommunications technologies, students generally professed little expertise in networking. In the aggregate, concept pre-test scores are consistent with self-assessments. There is no correlation between perceived expertise and pre-test performance.







At the aggregate level, students self-assess research expertise at a level similar to their self-assessment in Windows and indicate a relatively high level of perceived expertise. Performance in the concepts pre-test, however, is much lower and is lower than performance in other topics with less perceived expertise (see hardware and networking). At the individual student level, there is no correlation

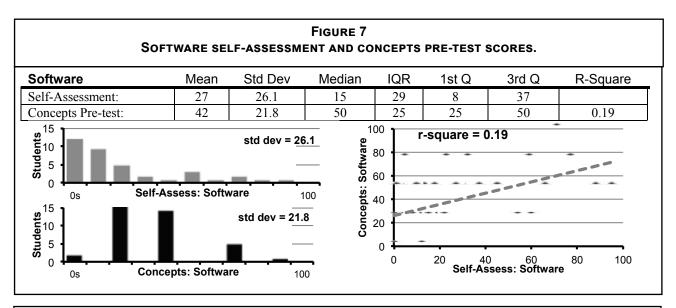
between self-assessed knowledge and concepts pre-test scores.

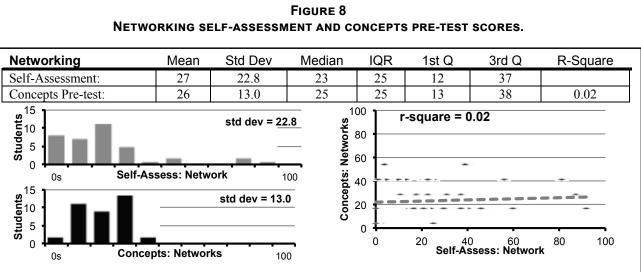
Review of aggregate data suggests most students profess little knowledge in the area of computer graphics with a few students indicating significant knowledge. Aggregate performance on the graphics pre-test is consistent with self-assessed knowledge. At the individual student level,

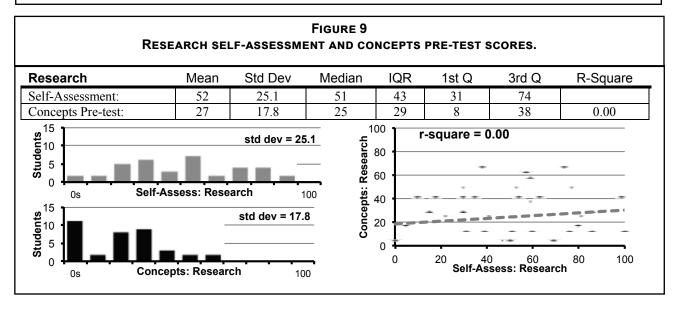
Spring 2015 (Volume 11 Issue 1)

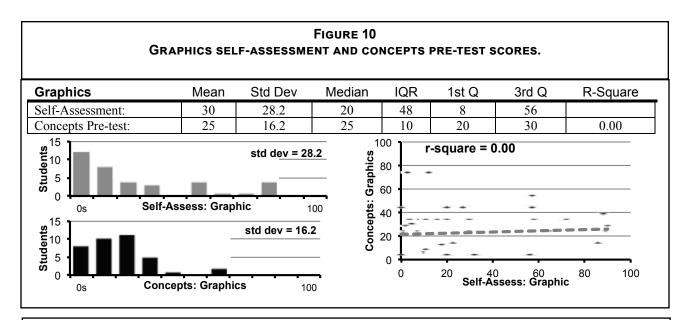
Journal of Learning in Higher Education

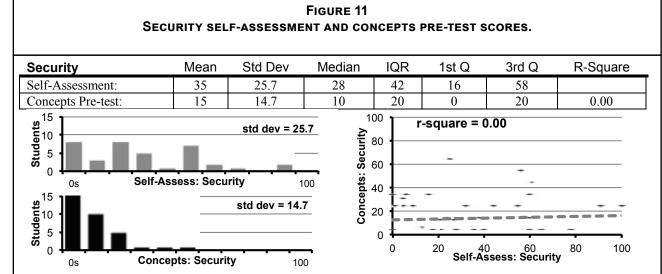
103











there is no correlation between self-assessed knowledge and concepts pre-test performance.

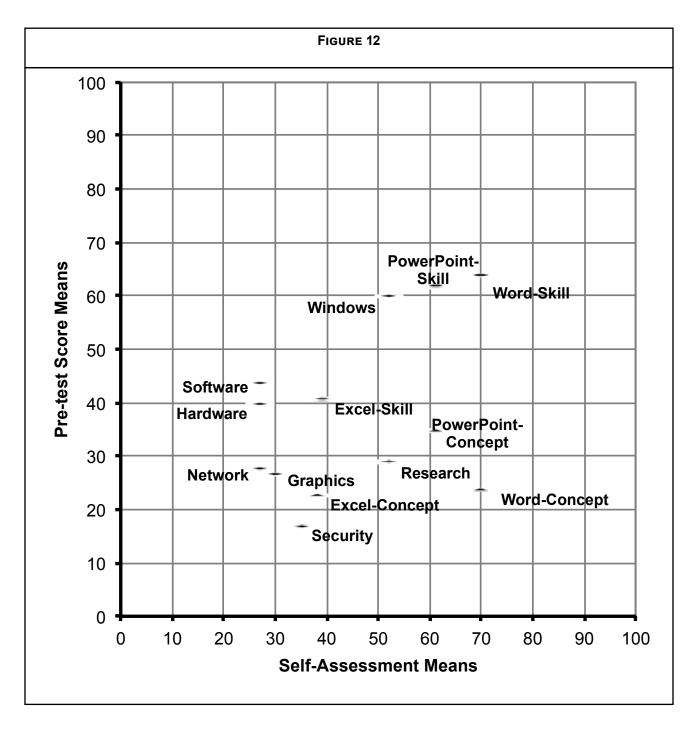
Review of aggregate data indicates some perception of knowledge in this topic. Concept pre-test scores, however, indicate the contrary. At the individual student level, there is no correlation between self-assessment and concept pre-test performance.

DISCUSSION

This research was conducted in a college course setting. This context is both a strength and a weakness for the study. Compared to experiments conducted outside the classroom, students are likely more engaged in the in-class survey and pre-tests integral to course instruction. On the other hand, the pre-tests are designed as part of an in-

structional process and are not be ideal instruments for a research experiment. For example, due to classroom time constraints, each topic had only four questions in the concepts pre-test. More questions per topic would have yielded more accurate and more statistically powerful results.

Another potential limitation to the study is the lack of well-understood standards of expertise in each content area. What did students think "significant knowledge" in these topics meant? Had the instructor provided a list of knowledge and skills inherent in the concept and skill pre-tests, students would likely have made more accurate self-assessments and correlations with pre-test scores would have been higher. However, the vagueness of standards is consistent with the purpose of the research. Proponents of the "digital native" meme present no standards of knowledge, simply attributing vague expertise to an age



cohort. This research requires students in that age cohort to tap into their own vague sense of knowledge in each of these topical areas.

Figure 12 plots the relationship between self-assessment and pre-test scores for each topic's distribution means. Note the marked gaps in plotted points between approximately 40 and 50 on both axes. The only topics students self-assessed above the level of 50 are Windows, Word, PowerPoint, and Research. The pre-test scores were above

50 only for Windows, Word-Skill, and PowerPoint-Skill. The remaining topics are below the 40 on both scales (with a minor exception for the Software pre-test score mean). Student self-assessment for Software, Hardware, Network, and Graphics are at 30 or lower.

These data patterns suggest students self-assess greater expertise in areas where they are active users. They perceive expertise in Windows, PowerPoint, Word and Research because they use Windows, PowerPoint, Word, and

Google on a frequent basis. Figure 12. Scatterplot of self-assessment and pre-test means.

And—for Windows, PowerPoint skills, and Word skills – they score significantly better in the pre-test than in other topics. As the Research pre-test questions involve a more sophisticated understanding of research processes than simply "googling," the Research pre-test scores were much lower than students' expectations.

It is important to note that pre-test scores for Word, Excel, and PowerPoint concepts are significantly lower than skills scores for those programs. These skills tests are comprised of small tasks and allow three opportunities to complete the question correctly before it is counted as incorrect. In such a trial-and-error testing environment, students can often manipulate the software correctly without understanding the underlying concepts. For example, a student might modify a pivot table in Excel by finding keywords from the question in the Excel ribbon without understanding the nature and use of pivot tables (an Excel concept). While students benefit from the multiple-choice nature of the concepts tests, they are not allowed multiple attempts to complete the question correctly. Thus, both skills and concept pre-tests likely overstate students' topic knowledge.

Finally, it should be noted that aggregate data tells a different story than individual data. Aggregate data, particularly expressed in the histograms of Figures 2 through 11, suggest varying patterns of student expertise among the different course topics. For example, Word and PowerPoint skills pre-test performance histograms look very similar to the self-assessment histograms for those topics while the histograms for Research look very different. There are real world interpretations to aggregate data patterns that are intuitively appealing. However, at the individual student level, data tell but one story - there is almost no correlation between student self-assessments and student pre-test performance. Out of thirteen coefficients of determination, only four are Ø.10 or higher (Word skills, Excel skills, PowerPoint skills, and Software concepts) and none of the r2 values reach 0.20. Although the aggregate data tell stories, these stories only emerge at the group level.

SUMMARY

To the extent students in this study represents the "digital native" population, there is little to support the digital native meme. These digital natives do not consider themselves knowledgeable in the standard topics found in college-level technology literacy courses nor are they particularly adept at assessing their own technological expertise.

REFERENCES

- Aiken, L. R. (1996). *Rating scales and checklists*. New York: John Wiley & Sons, Inc.
- American Library Association. (n.d.). Information literacy competency standards for higher education. Retrieved from http://www.ala.org/acrl/standards/informationliteracycompetency
- Bennett, S., Maton, K., & Kervin, L. (2008). The "digital natives" debate: A critical review of the evidence. *British Journal of Educational Technology*, 39(5), 775-786.
- Brown, C. C., & Czerniewicz, L. L. (2010). Debunking the "digital native": Beyond digital apartheid, towards digital democracy. *Journal of Computer Assisted Learning*, 26(5), 357-369.
- Brumberger, E. (2011). Visual literacy and the digital native: An examination of the millennial learner. *Journal of Visual Literacy*, 30(1), 19-47.
- CertiPort. (n.d.). IC3 GS4. Retrieved from http://www.certiport.com/Portal/common/pagelibrary/IC3_Certifications_GS4.html
- Helsper, E., & Eynon, R. (2010). Digital natives: Where is the evidence?. *British Educational Research Journal*, 36(3), 503-520.
- Margaryan, A., Littlejohn, A., & Vojt, G. (2011). Are digital natives a myth or reality? University students' use of digital technologies. *Computers & Education*, 56(2), 429-440.
- National Research Council. (1999). Being fluent with information technology. Washington DC: National Academy Press.
- Ng, W. (2012). Can we teach digital natives digital literacy? *Computers & Education*, 59(3), 1065-1078.
- O'Neil, M. (April 21, 2014). Confronting the myth of the 'digital native.' Chronicle of Higher Education. Retrieved from http://chronicle.com/article/Confronting-the-Myth-of-the/145949/
- Parsons, J., Oja, D. (2011). *Practical computer literacy*, 3rd ed. Boston: Course Technology.
- Prensky, M. (2001). Digital natives, digital immigrants. *On the Horizon*, 9(5).
- Shaffer, A., Carey, P., Finnegan, K., Pinard, K., Ageloff, R., Adamski, J., ..., Zimmerman, B. (2011). New perspectives on Office 2010: First course. Boston: Course Technology.

Spring 2015 (Volume 11 Issue 1)

Journal of Learning in Higher Education

107