Effect of Student Readiness on Student Success in Online Courses

Leah A. Geiger[A], Daphne Morris[B], Susan L. Suboez[C], Kay Shattuck[D], Arthur Viterito[E]

This research determined the effect of student readiness on student success in online courses that were of quality course design; were taught by experienced, engaging instructors; and were delivered within a well-supported and familiar Learning Management System (LMS). The research team hypothesized that student success in well-designed courses (those that meet the Quality Matters standards) and that are taught by experienced, engaging faculty is most influenced by student readiness factors, including individual attributes (such as motivation), life factors, comprehension, general knowledge, reading rate and recall, and typing speed and accuracy. A goal of the study was to determine which of these factors correlated most closely to student success. Results of this study indicated that, when course design, instruction, and LMS are held constant, only typing speed/accuracy and reading rate/recall were statistically significant as measured by the SmarterMeasure instrument and correlated to student course retention and course grade. Recommendations for further research are made.

Keywords: student readiness, course design, course retention, student success, online instructors

Student success in online learning continues to rightfully receive a lot of research and practice attention. That success has been measured by student satisfaction (Allen, Omori, Burrell, Mabry, & Timmerman, 2013; Aman, 2009), by levels of engagement (Hall, 2010), by grades (Swan, Matthews, & Bogle, 2010; Swan, Matthews, Bogle, Boles, & Day, 2011; Runyon, 2006), and by course persistence (Sherrill, 2012; Harkness, Soodjinda, Hamilton, & Bolig, 2011; Pittenger & Doering, 2010; Diaz & Cartnal, 2006; Dietz-Uhler, Fisher, & Han, 2007) and program retention (Boston, Ice, & Gibson, 2011). It is a complicated process to identify the correlations among the factors that influence student success. The impact of student characteristics (Moore & Kearsley, 2012; Jung, 2012; Poellhuber, Roy, & Anderson, 2011; Hall, 2011; Battalio, 2009; Wojciechowski & Palmer, 2005), of online learning experience (Adkins, 2013; Sherrill, 2012; Boston, Ice, & Burgess, 2012), of the design of a course (Naidu, 2013), of institutionally provided academic, counseling (Curry, 2013), and technical supports (Jung, 2012), of the skills and engagement of the

[A] College of Southern Maryland

[B] College of Southern Maryland

[C] College of Southern Maryland

[D] Director of Research, Quality Matters Program

[E] College of Southern Maryland

instructor (Stavredes & Herder, 2013; Jung & Latchem, 2012; Swan, 2012; Rutland & Diomede, 2011), and of familiarity with technology have been identified as impacting the success of online student learning.

This research project stemmed from a recommendation coming out of a study conducted by Jurgen Hilke (2010) for Maryland Online. He inquired as to why students withdraw from online classes. Four clusters of related factors were identified as obstacles for students completing an online course: (1) student chooses too many courses; (2) student gets behind in the course; (3) student experiences personal and family-related problems; and (4) student cannot cope with the combined workload of employment and academic studies (p. 7). As a result of these findings, he recommended further investigation into "an analysis of variables for inclusion into a potential regression model to predict online course retention" (p. 9). Student orientation to distance learning was one of the areas of possible intervention recommended. This research was inspired by Hilke's call for a further analysis of intervening variables.

The College of Southern Maryland (CSM) is a regionally accredited community college located in the mid-Atlantic, serving three counties of mixed social and economic demographics. CSM was one of the Maryland community colleges, that in 2002, field-tested what would become the Quality Matters Rubric™ and process for the continuous improvement of online learning. CSM is committed to strengthening quality assurance for students, faculty, and community with specific focus on continuing to design and to have all CSM online courses meet Quality Matters (QM) standards.

The SmarterMeasure™ student readiness assessment was identified as a vetted instrument to provide analysis of a number of variables identified in the Hilke study that might impact success in online courses. SmarterMeasure Learning Readiness indicator is a web-based tool to access a learner's likelihood for succeeding in an online and/or technology-rich learning program (para. 1). Previously, Argosy University had conducted research using SmarterMeasure and found "statistically significant relationships of technical competency, motivations, availability of time, and retention" (SmarterMeasures, Research Results, para. 4). The CSM study originated as a replication and extension of the Argosy study by collecting data from courses that meet QM standards (defined as a well-designed online course), and that were taught by experienced online instructors with established positive track records of student engagement and who were highly trained in the LMS and instructional design. The rationale for including these inputs to quality online learning was to hold constant three known influencing factors in student success: course design, instructor engagement, and familiarity and support of technology (LMS). The intent of this research was to determine the effect of student readiness on student success in online courses. The aim of this research project was to offer direction for student remediation in order to better prepare students for online learning and enhance student success, while noting the possible impact of course design and engaging instructor recommendations to enhance the quality of online learning.

Methodology

The study was conducted over two semesters. The disciplines of the courses varied (Fundamentals of Physics, Introduction to Sociology, and Applied Business Communications), but were first-year college courses. All three instructors had over seven years of online teaching experience each teaching online and had established student engagement skills. Additionally, all three had successfully completed at least two QM professional development trainings, were certified QM Master Reviewers, and had been active participants in the Middle States accreditation process.

Participants

The data collected in this study occurred in 11 classes with a total of 200 students over the period of two semesters – Fall 2012 and Spring 2013. Students were required to take the SmarterMeasure Learning Readiness Indicator before beginning the course work. The Indicator is a vetted web-based tool which assesses a learner's likelihood for succeeding in an online and/or technology-rich learning program by measuring the degree to which an individual student possesses attributes, skills, and knowledge that contribute to success. At the end of the semester, a correlational analysis was run to measure the relationships between SmarterMeasure scores and measures of course retention and grade distribution as measures of academic success. The study was conducted for two semesters to ensure a valid data pool.

SmarterMeasure data for six indicators were aggregated based on a percentage scale of 0% to 100%. The six indicators include On-screen Reading Rate and Recall; Typing Speed and Accuracy; Life Factors; Technical Knowledge; Reading Comprehension; and Individual Attributes (including motivation, procrastination, and willingness to ask for help). The final grades earned for the selected CSM courses was aggregated and rated by academic success. The findings were analyzed through Chi square tests for statistical significance. At the end of the semesters, we conducted a statistical analysis to measure the relationships between SmarterMeasure scores and CSM measures of course retention and grade distribution as measures of academic success.

Statistical Analysis

A Chi squared analysis was conducted to search for statistical significance to the scores of the SmarterMeasure assessment compared to the final course grades the students earned in the selected course sections. The six SmarterMeasure indicators scores were aggregated and compared to the final grade the individual student earned in the course. SmarterMeasure scores rely on student answers, some being subjective (life factors and individual attributes) as well as objective measures.

The scores from the SmarterMeasure assessment are delivered as ranges being labeled blue for rates between 85% and 100%; labeled green for rates between 70% and 84%; and labeled red for rates between 0% and 69%. As we analyzed the data, we realized that (a) there were a number of small cells, and (c) there were "zero" cells. Therefore, as per acceptable social statistical analysis, the only practical alternative was to combine categories in such a manner as to eliminate these small and zero cells. The red cells were highly problematic in most of the cases; therefore, we combined the green and red labels (frequencies) to eliminate any biasing that the low red frequencies may have introduced into the analysis. Therefore, we used two SmarterMeasure Indicator Rates – (a) students earning a rate from 85% to 100% (the blue labels), and (b) students earning a rate from 0% to 84% (the green and red labels, combined).

The final grades for the class were measured as "successful" at the rate of 70%

or higher, equating to a letter grade of C, B, or A. CSM policy supports this valuation, as 70% is the cut-off score for credit being earned for the course as well as its ability to be transferred to another school. In addition, the majority of student learning outcomes assessments at CSM use the benchmark of 70% or higher.

Results

At the 95% confidence level, two of the SmarterMeasure indicators (typing speed/accuracy and reading rate/recall) were statistically significant, thereby exerting significant influence on student success in the course. There is a high probability (at the 95% level) that the other SmarterMeasure indicators did not exert significant influence on student success. See Table 1 for the aggregate data.

SmarterMeasure Indicator, Reading Rate

The results for reading rate and recall indicate with a high degree of confidence that this indicator exerts an influence on student success. Specifically, 72 students were successful per the SmarterMeasure Indicator, while 62 ended up being successful in the course. The results are statistically significant, $\alpha = .05$. See Figure 1.

SmarterMeasure Indicator, Typing Speed

The results for typing speed and accuracy indicate with a high degree of confidence that this indicator exerts an influence on student success. Specifically, 88 students were successful per the SmarterMeasure Indicator, while 81 ended up being successful in the course. The results are statistically significant, $\alpha = .05$. See Figure 2.

SmarterMeasure Indicator, Life Factors

The results for life factors do not show that this indicator exerts an influence on student success. The results are not statistically significant, $\alpha = .05$. (Note that there is a statistical significance only if you set the alpha at the .1 level.) See Figure 3.

SmarterMeasure Indicator, Technical Knowledge

The results for technical knowledge do not show that this indicator exerts an influence on student success. The results are not statistically significant, $\alpha = .05$. (Note that there is a statistical significance only if you set the alpha at the .1 level). See Figure 4.

SmarterMeasure Indicator, Reading Comprehension

The results for technical knowledge do not show that this indicator exerts a significant influence on student success, as the results are not statistically significant, $\alpha = .05$. See Figure 5.

SmarterMeasure Indicator, Individual Attributes

The results for individual attributes do not show that this indicator exerts an influence on student success. The results are not statistically significant, $\alpha = .05$. See Figure 6.

Discussion

The study was based on the hypothesis that student success in well-designed courses (those that meet QM standards), that are delivered via a familiar LMS, and that are taught by experienced and engaging online instructors are most influenced

Table 1. SmarterMeasure Indicators Compared to Final

Indicator Name	Final Grade Earned	Indicator Rate at 85% to 100%	Indicator Rate at 0% to 84%	Total (N)
Reading Rate*	Successful	**62**	12	74
	Not Successful	10	6	16
	Total	**72**	18	**90**
Typing Speed*	Successful	**81**	59	140
	Not Successful	7	14	21
	Total	**88**	73	**161**
Life Factors	Successful	**49**	122	171
	Not Successful	4	25	29
	Total	**53**	147	**200**
Technical Knowledge	Successful	**95**	74	169
	Not Successful	21	7	28
	Total	**116**	81	**197**
Reading Comprehension	Successful	**144**	26	170
	Not Successful	24	4	28
	Total	**168**	30	**198**
Individual Attributes	Successful	**26**	145	171
	Not Successful	5	24	29
	Total	**31**	169	**200**

Note: "Indicator Name" refers to the SmarterMeasure Indicators. "Successful" in the Final Grade Earned column is based on the Institutional benchmark of earning a 70% or higher (A, B, or C letter grade). "Not Successful" is based on the Institutional benchmark of earning a 69% or lower (D or F letter grade).

*Reading Rate and Typing Speed are statistically significant, $\alpha = .05$, while the other SmarterMeasure Indicators are not statistically significant, $\alpha = .05$.

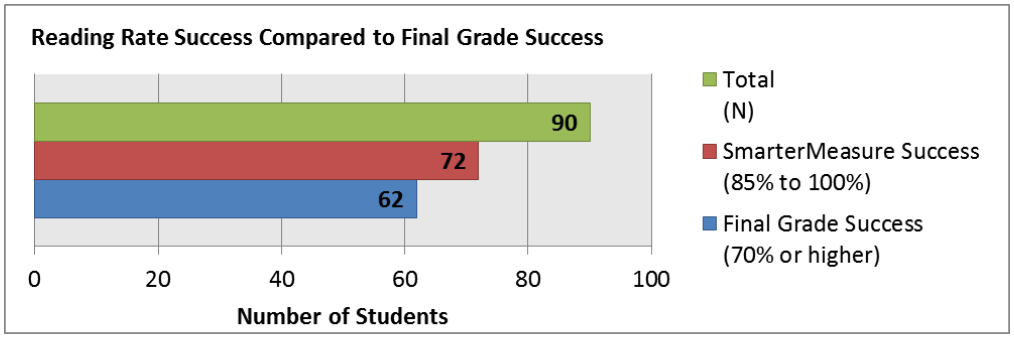

Figure 1. Reading rate success comparison

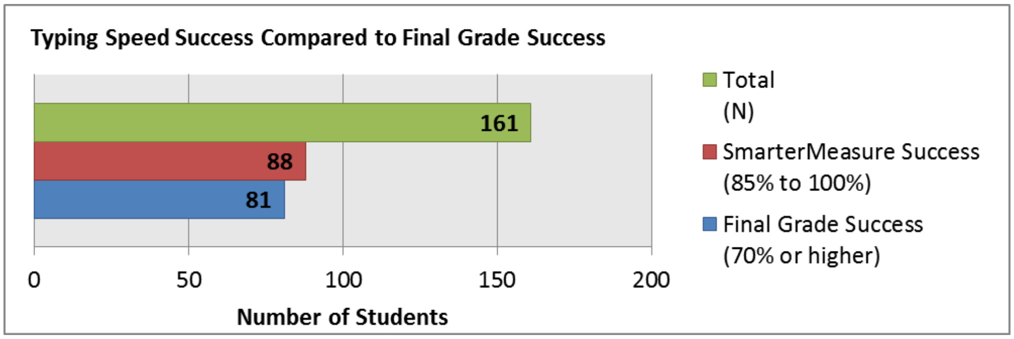

Figure 2. Typing speed score comparison

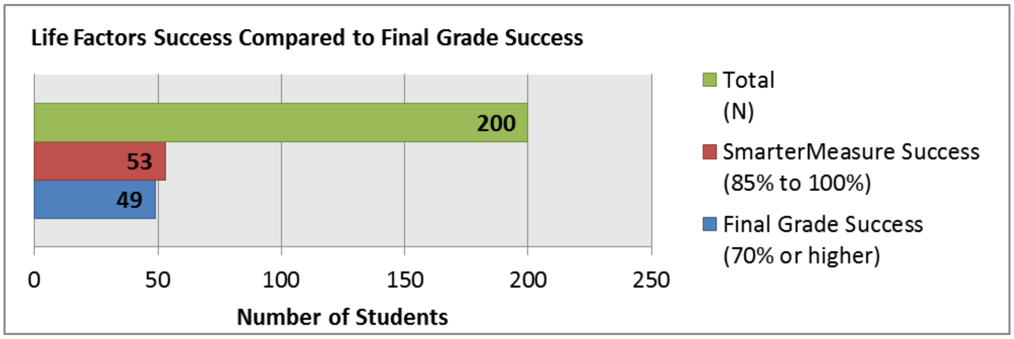

Figure 3. Life factors score comparison

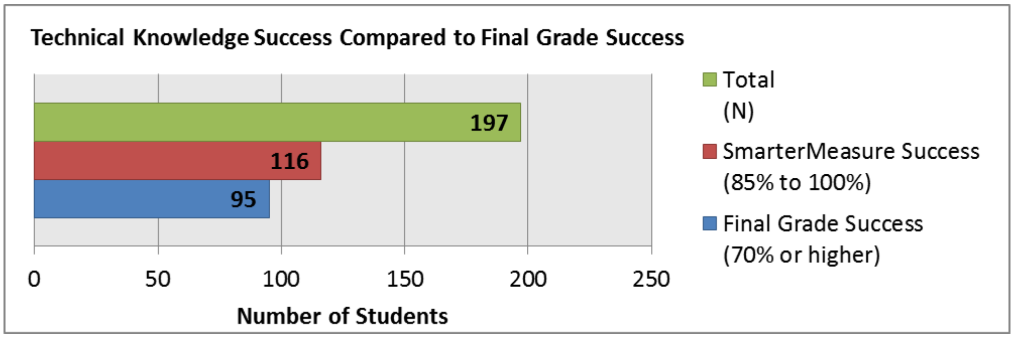

Figure 4. Technical knowledge score comparison

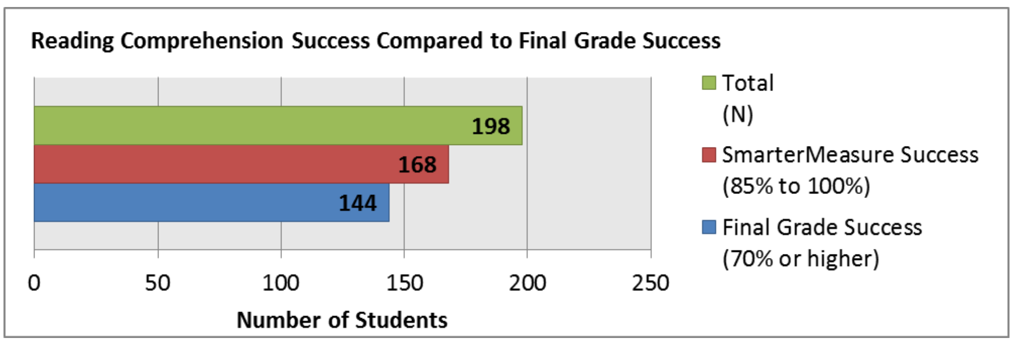

Figure 5. Reading comprehension score comparison

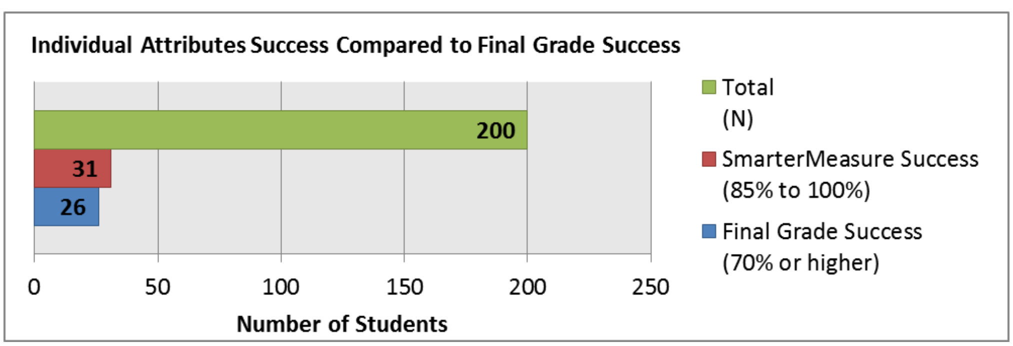

Figure 6. Individual attributes score comparison

by student readiness factors, including individual attributes (such as motivation), life factors, learning styles, technical competency, technical knowledge, reading rate and recall, and typing speed and accuracy. Based on the results of the study, most of our hypothesis was not supported.

Only two of the SmarterMeasure indicators (Reading Rate and Typing Speed) were statistically significant, thereby exerting an influence of student readiness on student success in these particular online courses. There are two limitations to consider. First, the sample size was small. Second, there can be alternative interpretation for these results. For example, a higher typing speed with accuracy may be indicative of a student's expertise with computer technology. A higher typing speed with accuracy may also be indicative of a student's attention to detail, and it is the attention to detail factor that exerted an influence on student success. An additional possibility is that higher typing speeds were developed from experience in previous online courses, and success in previous online courses has been identified as a predictor of success (Boston, Ice, & Burgess, 2012). The possible impact of previous student success in online courses was not explored during this study and would be an additional source for correlation in readiness.

In this controlled study, two indicators (Life Factors and Technical Knowledge) were not statistically significant unless the alpha level is lowered from $\alpha = .05$ to $\alpha = .01$. The last two indicators (Reading Comprehension and Individual Attributes) were not statistically significant. The small sample size may have affected the results. An important caveat from this study is that these findings come from students in courses that meet quality standards for course design and were taught by experienced, engaging online instructors. It could be important to further explore the impact of quality course design and engaging faculty on student readiness factors, especially those identified by SmarterMeasure.

Our findings differ from the Argosy University study, "SmarterServices" (2011). The Argosy study found the following SmarterMeasure indicators have statistically significant impact on student success: technical competency, motivation, availability of time, and retention (SmarterServices). Two factors may have contributed to the different findings. First, our small sample size may have affected our results compared to the Argosy study. Second, our study controlled for the course design, teaching, and LMS variables compared to the Argosy study; therefore, our results may be more focused.

The current study allowed a closer analysis of student readiness by controlling three variables: (a) the course design was considered high quality, as only courses that had previously met QM standards were used; (b) the LMS utilized was industry-standard and was familiar to students and instructor; and (c) the faculty participating in the study have strong, positive track records of student engagement, and were highly trained in the LMS and instructional design. We caution generalization of these findings to conclude that only typing speed/accuracy and reading rate/recall are important to the successful completion of an online course.

Suggestions for Future Research

The sample size could be broadened to increase validity and reliability, thereby leading to institutional policy changes, such as a mandatory student orientation course or standardized modules for all online courses that incorporate resources for typing and/or reading rate practice. The study could be easily replicated for extended statistical analysis using our methodology or utilizing other designs, such as a matched pair design. Another approach to increase the sample size would be to expand the study to multiple institutions/instructors with similar characteristics as the original institution in the first study. We would alert future researchers to control the inputs of quality course design and experienced, engaging online instructors.

This study was quantitative. Qualitative information could be gathered and analyzed (1) to discover other indicators of student success and (2) to test alternative analyses. For example, students who complete the SmarterMeasure instrument, perhaps as an online learning orientation (Koehnke, 2013), may be more likely to complete class work leading to student success compared to the students who elect not to complete the required SmarterMeasure instrument. Focus groups of student participants in a replicated study would add additional depth to any findings, as would using educational analytics to determine if any correlations exist between students previous online course success and readiness factors.

Another avenue of study would be to explore the actions of experienced, engaging online instructors teaching of the courses. It could be enlightening to learn if the highly skilled online instructors in this study mitigated the impact of the four other readiness factors measured that were not found statistically significant (life factors, individual attributes, technical knowledge, and reading comprehension). The findings could reveal a snapshot of pedagogical habits that promote student success in the online classroom.

The data for Life Factors and Individual Attributes indicate that a large number of students ranked at the 0% to 84% level. In this study of the 200 students, 147 ranked within 0% to 84% for Life Factors, while 53 ranked at the upper level and 169 ranked within 0% to 84% for Individual Attributes, while 39 ranked at the upper level. A future study could compare these online student rankings with students taking comparable courses using other delivery methods (e.g., face-to-face, web-hybrid). The results should also be compared to success factors in different disciplines using a matched pair experiment. For example, how does an English course, where reading comprehension is critical, compare to courses in other disciplines.

In addition, future studies could compare results from QM-certified courses to courses that have not been designed using QM standards. Likewise, a study could compare the results of less experienced with those of higher-skilled, experienced online instructors.

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