SmarterServices™

SmarterMeasure™ Research Findings for Sample University

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SmarterMeasure™ Research Findings

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Executive Overview

Multiple measures were used to calculate the relationship between SmarterMeasure scores and the constructs of academic success, retention, engagement, and satisfaction. Statistically significant relationships were found between SmarterMeasure scores and each of these four constructs.

Academic Achievement and Retention were compared to SmarterMeasure scores using grade and enrollment data.

- The measures of Individual Attributes, Technical Knowledge, and Life Factors had statistically significant mean differences with the measures of GPA.
- The measure of Learning Styles had a statistically significant mean difference between students who were retained and those who left. A 73% classification accuracy of this retention measure was achieved.
- The measures of Individual Attributes and Technical Knowledge were statistically significant predictors of retention as measured by the number of courses taken per term.

Satisfaction and Engagement were compared to SmarterMeasure scores using students' responses to an online survey.

- The measures of Individual Attributes and Life Factors had statistically significant mean differences on six of the seven survey items. Reading Rate, Technical Knowledge, and Technical Competency had significant differences on four of the seven items.
- The measures of Individual Attributes and Technical Competency had statistically significant relationships with the four survey items related to Engagement. The items of hours per week spent on course related activities; number of times per week logging into course; length of discussion board postings; and number of times contacting technical support can be predicted given knowledge of Individual Attributes, and more specifically the subscales listed.
- The measures of Life Factors, Individual Attributes, Technical Competency, Technical Knowledge, and Learning Styles were used to correctly classify responses to the survey questions related to engagement and satisfaction with up to 93% classification accuracy.
- Structural equation modeling was used to create a hypothesized theoretical model to determine if SmarterMeasure scores would predict satisfaction as measured by the survey. Results indicated that prior to taking online courses, student responses to the readiness variables were important indicators of later student satisfaction/retention. The structural coefficient for Ready predicting Satisfy, $\Gamma = .36$, was statistically significant ($z = 6.01$, $p = .0001$). Therefore, the multiple SmarterMeasure assessment scores are a statistically significant positive predictor of the survey responses.

Further analysis revealed that the predictive nature of SmarterMeasure scores as classified by the Readiness Ranges can be improved using recommended adjustments to the grading thresholds.

The majority of survey participants (90%) either somewhat or definitely remembered taking the assessment. The majority of survey participants (89%) found the assessment somewhat useful, useful, or very useful; while only 11% did not find it useful at all as a student service.

Background

Usage of SmarterMeasure by Sample University

Since 2007, several campuses of Sample University have used the SmarterMeasure™ Learning Readiness Indicator. More than 25,000 students from these campuses have taken the SmarterMeasure assessment.

The SmarterMeasure™ Learning Readiness Indicator is an online assessment of a learner's level of readiness for studying in an online or technology enriched environment. The assessment quantifies the learner's "goodness of fit" for learning in these modalities. Rather than being used as a gate keeper to prohibit learners from enrolling in these types of courses, it is a diagnostic device to identify learners who may be at-risk so that the school can provide appropriate services for remediation and/or support. The prior name of the assessment was READI – Readiness For Education At a Distance Indicator. At Sample University, the assessment is most often still referred to as READI. For this reason, the survey questions referred to the assessment as READI.

SmarterMeasure is designed to be a student service tool. In an optimal implementation plan someone at the school such as an orientation course instructor, academic advisor, or enrollment counselor discusses the learner's SmarterMeasure scores with them. While there are general resources for remediation and support provided in the score report, the strongest gains can be made when the SmarterMeasure scores are used as a discussion starter to then make the student aware of the resources for remediation and support that the school provides. SmarterMeasure is designed to be the diagnostic tool, not the full remediation and support system.

SmarterMeasure is a 124-item assessment that measures variables in the following scales: Individual Attributes, Life Factors, Learning Styles, Reading Skills, Technical Knowledge, Technical Competency, and Typing Skills. The appendix contains a list of the sub-scales and number of items within each of these scales.

Research Plan Data Points

Multiple Points of Measurement

The familiar story is told of several persons who were blindfolded and then allowed to feel a part of an elephant. Each of them described what they felt, but a complete understanding of the elephant could only be obtained from a synthesis of the observations of all of the blindfolded persons. Academic research is much the same in that any singular measurement of a phenomenon rarely provides a complete analysis. For the purposes of this research, several measures and statistical processes were used to measure the relationship between SmarterMeasure scores and variables of academic achievement, engagement, satisfaction, and retention

It should be noted that preferred primary data were not available for some of the items in this analysis. For example, preferred primary data for engagement would be metrics such as the numbers and length of discussion board postings and the number and frequency of clicks in a learning management system. However, collection of that data was beyond the scope of this project. Secondary level data in the form of a student self-reporting the levels of engagement was used. A recommendation for future study would be to replicate this analysis using as much primary preferred data as is available.

The following data points were used in this analysis:

Construct	Analysis	Data Sources
Academic Success What is the relationship between SmarterMeasure scores and learner's grades?	Analysis of Variance	• SmarterMeasure scores at the scale and sub-scale level • Student's grades in a specific course • Student's overall GPA
Student Engagement What is the correlation between SmarterMeasure scores and metrics of student engagement?	Independent Samples t-tests Discriminant Analysis	• SmarterMeasure scores at the scale and sub-scale level • Survey questions which prompted students to self-report levels of student engagement.
Student Satisfaction What is the relationship between SmarterMeasure scores and metrics of student satisfaction?	Independent Samples t-tests Discriminant Analysis Structural Equation Modeling	• SmarterMeasure scores at the scale and sub-scale level • Survey questions which prompted students to self-report levels of student engagement.
Student Retention What is the relationship between SmarterMeasure scores and metrics of student retention?	Independent Samples t-tests Discriminant Analysis Multiple Regression Correlation	• SmarterMeasure scores at the scale and sub-scale level • Student enrollment status data

Data Analysis Considerations

For the purposes of this analysis, it should be noted that correlations and other comparisons of means were calculated at the scale and sub-scale level. For example, in addition to correlating levels of student engagement to the scale score for Individual Attributes, a correlation could also be calculated for the sub-scale of motivation to student engagement.

To facilitate the comparisons of SmarterMeasure scores to other metrics of student success and satisfaction, a paired dataset was created. Identification variables included first and last name, email address, and demographic factors (age range, gender). SmarterServices produced the paired data set upon receipt of the student success and satisfaction data set form.

Timeline

This project was conducted during the Summer of 2011. The first phase involved the collection of data from the SAMPLE UNIVERSITYstudent information system. This data set containing measures of academic success and retention was then matched with SmarterMeasure scores. The second phase was the conducting of a survey to allow students to report measures of satisfaction and engagement. The final phase was the statistical analysis and report production.

Quantitative Student Feedback

A useful metric of the impact of SmarterMeasure is a study to determine the degree to which a student's SmarterMeasure scores are indicative of their experience in an online or technology-rich course. The following questions were used to quantify the learner's experience and then these ratings were correlated to the SmarterMeasure scale and sub-scale scores. These questions were asked on a seven-point likert type scale ranging from strongly agree to strongly disagree.

Post-Course Survey Item	*Category*	*SmarterMeasure Scale Score*
It was easy for me to keep up with the reading required for my online course(s):	Academic Success	Reading Rate and Recall
It was easy for me to find time to complete my online course(s):	Engagement	Life Factors
It was easy for me to complete my online course(s) with my level of computer skills:	Satisfaction	Technical Competency
It was easy for me to find a good place to study for my online course(s).	Engagement	Life Factors
Generally speaking, online courses are a good choice for me:	Satisfaction	Individual Attributes

I would take another online course in the future:	Retention	Learning Styles
It was easy for me to complete my online course(s) with my level of typing abilities.	Engagement	Typing Rate and Accuracy

Third Party Analysis

To ensure integrity in the data analysis, the services of a third-party company was used to conduct the data analysis. Applied Measurement Associates, an independent research firm in Tuscaloosa, Alabama, was contracted for this project. Statisticians from Applied Measurement Associates are familiar with data from SmarterMeasure because they have worked on projects with SmarterMeasure data prior to this assignment.

Survey

Survey Methodology

Data relative to academic success and retention was collected from the SAMPLE UNIVERSITY student information system. Data relative to engagement, retention, and satisfaction was collected using an online survey. These data points were combined on an individual student level with SmarterMeasure scores which included Life Factors, Learning Styles, Personal Attributes, Technical Competency, Technical Knowledge, Reading, and Typing Accuracy. Together several analyses were conducted to determine relationships between the variables. These included independent t-tests, analysis of variance, multiple regression, correlation, discriminate analysis, and structural equation modeling.

At the time of the beginning of this project, a total of 22,316 students of Sample University schools had taken the SmarterMeasure assessment. The Information Technology Department at SAMPLE UNIVERSITY was able to match the SmarterMeasure records to 19,742 students. The initial invitation to participate email was sent on July 12, 2011, to 19,742 students from Sample University schools which had taken the SmarterMeasure assessment. Eight hundred forty-one of these emails bounced, and 133 students requested to opt-out and not be contacted again about the survey. The total accessible population was 18,768. After two reminders to non-respondents, the survey was closed on July 25, 2011. An incentive of a drawing for a free iPad was provided to boost participation rates. According to the Morris Gold Sample Size Table, an accepted guideline for determining the smallest acceptable sample size, a return of 379 records was required for the sample size to be considered adequate. A total of 587 responses to the survey were received (N=587).

Representative Sample

Since the return rate was low on the survey, a comparison of means analysis was conducted to determine if the 587 records were a representative sample of the larger total accessible population. Of the students who did return the survey, the average GPA was 2.74. Of those who did not return the survey, the GPA was 2.54. Of the students who did return the survey, the average number of courses taken per term was 2.95. Of the students who did not return the survey, the average number of courses taken per term was 2.93. One can conclude from this comparison that the survey respondents are a representative sample of the larger accessible population.

Findings

A survey was administered to Sample University students who had taken the SmarterMeasure™ Learning Readiness Indicator to ask key questions regarding an online student's learning experience (Appendix). In addition, important variables that indicate a student's readiness to take online courses was paired with these survey responses. The readiness variables were: *Life Factors, Learning Styles, Personal Attributes, Technical Competency, Technical Knowledge, Reading, and Typing Accuracy*. These readiness variables contained subscales listed in the Appendix. Together several analyses were conducted to determine relations between the variables.

This section of the report is grouped by the following types of statistical analysis:
independent t-tests, analysis of variance, multiple regression, correlation, discriminate analysis, and structural equation modeling.

Independent t-test Analysis

Two groups were formed based upon the survey questions. Basically, the 0 (neutral) to 6 (strongly agree) such that 0, 1, 2, and 3 were coded as 0 = negative response and 4, 5, and 6 were coded as 1 = positive response. This effectively dichotomizes two very different groups of students. It would be important to know if these two groups of students differed on the Smarter Measure readiness indicator variables. The following tables display an independent t-test analysis for mean differences on the readiness variables for each survey question by these two distinctly different groups.

Question 1. It was easy for me to keep up with the reading required in my online course(s).

Results show that *Individual Attributes, Reading Rate, and Life Factors* played a role in indicating the student's mean difference between negative and positive students for ease of keeping up with reading required in the online course (Table 1).

Table 1. Independent t-test for Mean difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	1.34	276	.18	2.97	2.21
Individual Attributes	2.01	276	.045	1.97	.97
Reading Rate	2.06	276	.04	58.38	28.33
Typing Accuracy	.28	276	.77	.68	2.39
Technical Knowledge	.108	276	.91	.19	1.78
Life Factors	2.17	276	.03	2.85	1.32
Technical Competency	.93	276	.36	1.43	1.55

Question 2. It was easy for me to find time to complete my online course(s).

Results show that *Individual Attributes and Life Factors* played a role in indicating the student's mean difference between negative and positive students for ease of finding time to complete the online course (Table 2).

Table 2. Independent t-test for Mean Difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	.80	276	.42	1.62	2.01
Individual Attributes	3.24	276	.001	2.84	.88
Reading Rate	1.12	276	.26	29.01	25.82
Typing Accuracy	.16	276	.88	.34	2.17
Technical Knowledge	1.62	276	.11	2.60	1.61
Life Factors	2.63	276	.009	3.12	1.19
Technical Competency	.58	276	.56	.81	1.41

Question 3. It was easy for me to find a good place to study for my online course(s).

Results show that *Individual Attributes and Life Factors* played a role in indicating the student's mean difference between negative and positive students for ease of finding a good place to study for online courses (Table 3).

Table 3. Independent t-test for Mean Difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	.06	273	.95	1.62	2.01
Individual Attributes	2.90	273	.004	2.84	.88
Reading Rate	.65	273	.519	29.01	25.82
Typing Accuracy	1.34	273	.182	.34	2.17
Technical Knowledge	1.51	273	.131	2.60	1.61
Life Factors	3.48	273	.001	3.12	1.19
Technical Competency	1.70	273	.090	.81	1.41

Question 4. It was easy for me to complete my online course(s) with my level of computer skills.

Results show that *Individual Attributes, Life Factors, and Technical Competency* played a role in indicating the student's mean difference between negative and positive students in the level of computer skills to complete an online course (Table 4).

Table 4. Independent t-test for Mean Difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	.99	276	.32	3.06	2.01
Individual Attributes	3.44	276	.001	4.61	.88
Reading Rate	.37	276	.71	14.54	25.82
Typing Accuracy	.41	276	.68	1.37	2.17
Technical Knowledge	1.31	276	.19	3.25	1.61
Life Factors	3.43	276	.001	6.21	1.19
Technical Competency	2.91	276	.004	6.17	1.41

Question 5. Generally speaking, online courses are a good fit for me.

Results show that *Individual Attributes, Technical Knowledge, and Life Factors* played a role in indicating the student's mean difference between negative and positive students in whether online courses were a good fit for them (Table 5).

Table 5. Independent t-test for Mean Difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	1.68	276	.09	3.21	1.91
Individual Attributes	5.42	276	.0001	4.38	.81
Reading Rate	1.44	276	.15	35.47	24.56
Typing Accuracy	.46	276	.65	.95	2.07
Technical Knowledge	2.21	276	.028	3.38	1.53
Life Factors	3.88	276	.0001	4.33	1.12
Technical Competency	.56	276	.58	.74	1.34

Question 6. I would take another online course in the future.

Results show that *Individual Attributes, Technical Knowledge, and Life Factors* played a role in indicating the student's mean difference between negative and positive students in whether online courses were a good fit for them (Table 6).

Table 6. Independent t-test for Mean Difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	1.67	274	.09	3.23	1.94
Individual Attributes	4.66	274	.0001	3.88	.83
Reading Rate	.51	274	.61	12.70	25.03
Typing Accuracy	1.60	274	.11	3.35	2.09
Technical Knowledge	2.37	274	.019	3.67	1.55
Life Factors	3.96	274	.0001	4.49	1.13
Technical Competency	.07	274	.94	.10	1.36

Question 7. If I am having trouble in an online course, I would ask the instructor for help.

Results show that *none* of the Readiness Variables had a statistically significant mean difference between the two groups (negative and positive students) on Question 7 (Table 7).

Table 7. Independent t-test for Mean Difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	.95	271	.34	2.64	2.78
Individual Attributes	1.14	271	.25	1.41	1.23
Reading Rate	.09	271	.93	12.70	36.65
Typing Accuracy	.76	271	.45	3.12	3.08
Technical Knowledge	1.15	271	.25	2.33	2.22
Life Factors	1.11	271	.27	2.54	1.68
Technical Competency	.23	271	.82	.42	1.85

Retention

The *School Status* variable was coded into two distinct groups based on those who left the university and those who were retained. Basically, dismissal, graduate, leave of absence, NDS-fulfilled, probation, standard period of non-enrollment, transfer to other campus, transfer to other program, and withdraw were coded as 0 (zero), while active, externship, NDS-active, original enrollment, pending graduate were coded as 1 (one). This created an important retention variable to determine if mean differences exist on the readiness Variables. The number of students per category who were retained (N = 235) were: active (228), pending graduate (2), original enrollment (4), NDS-active (1). The number of students per category who were non-completers or left (N = 96) were: withdraw (33), probation (9), transfer to other campus (1), transfer to other program (44), dismissal (3), leave of absence (5), standard period of non-enrollment. The cutoff was set at 70% for classification purposes based on sample size per group.

Results show that *Learning Styles* had a statistically significant mean difference between those who left and those who were retained (Table 8). A discriminant analysis further showed that only *Learning Styles* played a role in predicting group membership ($F = 3.89$ (1,241); $p < .05$). The classification table is in Table 9. A 73% classification accuracy was achieved.

Table 8. Independent t-test for Retention Mean Difference in Readiness Variables

Readiness Variable	t	df	P value	Mean Difference	Std. Error Difference
Learning Styles	2.28	310	.023	3.57	1.57
Individual Attributes	.30	310	.764	.22	.72
Reading Rate	.24	310	.809	5.93	24.56
Typing Accuracy	1.02	310	.306	1.75	1.71
Technical Knowledge	.61	310	.545	.79	1.31
Life Factors	1.43	310	.155	1.53	1.07
Technical Competency	.14	310	.886	.16	1.13

Table 9. Discriminant Analysis Retention Classification Based on Learning Styles

Retention Group	Predicted Group Membership		Total
	Left	Retained	
Left	1	64	65
Retained	1	177	178

Summary

The following questions from the Survey (Table 10) indicated that *Individual Attributes and Life Factors* play a key role in student online satisfaction, while *Learning Styles* differentiated retention status (left school versus retained in school).

Table 10. Independent t-test Findings for Survey Questions.

Survey Questions	Smarter Services Variable
It was easy for me to keep up with the reading required in my online course(s).	*Individual Attributes, Life Factors* *Reading Rate*
It was easy for me to find time to complete my online course(s).	*Individual Attributes, Life Factors*
It was easy for me to find a good place to study for my online course(s).	*Individual Attributes, Life Factors*
It was easy for me to complete my online course(s) with my level of computer skills.	*Individual Attributes, Life Factors* *Technical Competency*
Generally speaking, online courses are a good fit for me.	*Individual Attributes, Life Factors* *Technical Knowledge*
I would take another online course in the future.	*Individual Attributes, Life Factors* *Technical Knowledge*
If I am having trouble in an online course, I would ask the instructor for help.	None
Retention	*Learning Styles*

Analysis of Variance

GPA Group

GPA was categorized into groups to determine if level of GPA had a mean difference in the readiness Variables. Basically, 0 = .99 or less, 1 = 1 to 1.99, 2 = 2 to 2.99, 3 = 3 to 3.99, 4 = 4 to 4.99. Table 11 shows the results for the group mean differences in the SmarterMeasure variables. Similar to the independent t-test findings, *Individual Attributes*, *Technical Knowledge*, and *Life Factors* played a role in GPA category differences.

Table 11. One-way Analysis of Variance for GPA Group

SmarterMeasure Variable	F	P value
Learning Styles	.69	.60
Individual Attributes	2.42	.05
Reading Rate	.33	.86
Typing Accuracy	.65	.63
Technical Knowledge	2.37	.05
Life Factors	2.23	.055
Technical Competency	1.84	.12

Multiple Regression Analysis

An important question is whether the number of courses per term can be predicted given knowledge of other variable information. The frequency for the number of courses taken per term are in Table 12. It forms an expected distribution with 3 courses per term being the norm. What variables predict this enrollment? Table 12 indicates that *Individual Attributes, Technical Knowledge, and GPA* are significant predictors for number of courses taken per term.

Table 12. Number of Courses Taken per Term

Number of Courses	Frequency	Percent
1	41	10.3
2	99	24.9
3	154	38.8
4	72	18.1
5	8	2.0
6	18	4.5
7	5	1.3
	397	100.0

Table 13. Regression Analysis for Number of courses per Term

Regression Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	7.527	.907		8.301	.0001
Individual Attributes	-.050	.011	-.239	-4.470	.0001
Technical Knowledge	-.012	.006	-.105	-1.968	.050
GPA	.133	.069	.098	1.928	.055

Engagement

Several questions were asked on the survey that were linked to student engagement. These questions were: 1) On average, how many hours per week do you spend on activities related to your online course?; 2) On average, how many times per week do you log into your online course?; 3) On average, when you make a discussion board posting in an online course, how many sentences long is it?; and 4) Approximately how many times have you contacted technical or student support to receive assistance as an online student? Do SmarterMeasure variables and/or their subscale variables predict these amounts? Results indicated:

Question 1: *Individual Attributes* significant, with specific subscales Locus of Control, Procrastination, and Time Management significant (Table 14).
Question 2: *Individual Attributes* significant, with specific subscale Procrastination significant (Table 15).
Question 3: *Individual Attributes* significant, with specific subscales Academic Attributes and Locus of Control significant (Table 16).
Question 4: *Individual Attributes and Technical Competency* significant with respective subscales Time Management and Internet Competency significant (Table 17).

Table 14. On average, how many hours per week do you spend on activities related to your online course?

Smarter Measure Variables	F (df1/df2)	P Value
Individual Attributes	23.32 (1,374)	.0001
Subscales	10.09 (3,393)	.0001
Locus of Control		
Procrastination		
Time Management		

Table 15. On average, how many times per week do you log into your online course?

Smarter Measure Variables	F (df1/df2)	P Value
Individual Attributes	6.21 (1,374)	.013
Subscale	12.25 (1,376)	.001
Procrastination		

Table 16. On average, when you make a discussion board posting in an online course, how many sentences long is it?

Smarter Measure Variables	F (df1/df2)	P Value
Individual Attributes	11.43 (1,370)	.001
Subscales	8.18 (2,369)	.0001
Academic Attributes		
Locus of Control		

Table 17. Approximately how many times have you contacted technical or student support to receive assistance as an online student?

Smarter Measure Variables	F (df1/df2)	P Value
Individual Attributes	3.93	.02
Technical Competency		
Subscales	5.44 (2,262)	.005
Time Management		
Internet Competency		

Summary

The number of courses taken per term can be predicted given knowledge of a student's *Individual Attributes, Technical Knowledge, and GPA* (F = 11.41 (3,353), p < .0001). *Individual Attributes* (with subscales listed) played a key role in Questions 1 to 4 prediction. Basically, hours per week spent on course related activities, number of times per week logging into course, length of discussion board postings, and number of times contacting technical support can be predicted given knowledge of *Individual Attributes*, and more specifically the subscales listed.

Correlation Analysis

The number of courses per term was correlated with the survey questions to determine if any statistically significant relations were present. Table 18 displays the correlations amongst the questions. Basically, the number of courses per term have *zero* correlation or association with any of the satisfaction survey questions.

Table 18. Correlation Between Number of Courses per Term and Survey Questions.

Survey	Number of Courses per Term	P Value
Question 1	-.03	.25
Question 2	.04	.23
Question 3	-.03	.25
Question 4	.02	.38
Question 5	-.06	.12
Question 6	-.04	.22
Question 7	-.02	.39

The number of courses per term was also correlated with the SmarterMeasure variables to determine if any statistically significant relations were present. Table 19 displays the correlations amongst the variables. Results indicated significant relations between number of courses per term taken and *Learning Styles, Individual Attributes, Reading Rate, Typing Accuracy, Technical Knowledge*, *and GPA.* These SmarterMeasure variables are therefore good indicators of how many courses a student takes per term.

Table 19. Correlation Between Number of Courses per Term and Readiness Variables.

Readiness Variables	Number of Courses per Term	P value
Learning Styles	-.02	.06
Individual Attributes	-.04	.003
Reading Rate	.11	.0001
Typing Accuracy	.02	.026
Technical Knowledge	-.04	.002
Life Factors	-.01	.33
Technical Competency	-.003	.42
GPA	.06	.0001

CONCLUSION

Table 20 summarizes together the findings for the independent t-test analysis comparing negative and positive students on the readiness variables, or for Retention, students who left versus those who were retained; as well as GPA Group. It becomes clear that *Individual Attributes* and *Life Factors* play a key role according to the survey questions. Question 1 was concerned with reading, therefore not surprising that *Reading Rate* was also important. Similarly, Question 4 dealt with competent computer skills, therefore not surprising that *Technical Competency* was also important.

Questions 5 and 6 refer to the key issue of whether an online course is a good fit and if they would take another online course. *Technical Knowledge* played an additional factor in these two questions.

A final grouping (retention) was created which contrasted left versus retained school status. A significant mean difference between these two groups was apparent for the *Learning Styles* of students.

Finally, *Individual Attributes, Technical Knowledge, and Life Factors* explained mean differences in the GPA groups.

Table 20. A comparison of independent t-test results

Variables	**Learning Styles**	**Individual Attributes**	**Reading Rate**	**Typing Accuracy**	**Technical Knowledge**	**Life Factors**	**Technical Competency**
Q1 Finish Reading		X	X			X	
Q2 Find Time		X				X	
Q3 Good Place		X				X	
Q4 Computer Skills		X				X	X
Q5 Good Fit		X			X	X	
Q6 Take Another		X			X	X	
Retention	X						
GPA Group		X			X	X	

The number of courses taken per term can be predicted given knowledge of a student's *Individual Attributes, Technical Knowledge, and GPA.* Correlation between number of courses taken per term and the survey questions revealed *no* statistically significant association. In contrast, correlation between the number of courses taken per term and the readiness variables demonstrated that many of the variables were significantly correlated. The readiness variables: *Learning Styles, Individual Attributes, Reading Rate, Typing Accuracy, and Technical Knowledge, and GPA* were good indicators of how many courses a student takes per term.

Discriminant Analysis

A discriminant analysis was performed on the seven survey questions with the SmarterMeasure readiness variables. The results indicated that certain readiness variables do discriminate between positive and negative group student learning experience responses.

Question 1. It was easy for me to keep up with the reading required in my online course(s).

Responses
47 (16% No) and 251 (84% Yes)

Significant Readiness Variables

Readiness Variable	F	P value	Function
Life Factors	10.213	.002	.977
Individual Attributes	4.638	.032	.658

Note: df = 1,296; Function indicates variable importance with Question 1.

Classification Results

Question 1	Predicted Group Membership		Total
	Negative	Positive	
No	1	46	47
Yes	1	250	251

Note: 84% correctly classified

Summary
Findings indicate that *Life Factors and Individual Attributes* were important readiness indicators of whether a student felt they could keep up with online reading requirements. In addition, knowledge of these two readiness indicators showed a 84% classification accuracy. Knowing that 46 students with negative responses were not correctly classified means that other information or variables would be important in determining their situation or response to Question 1.

Question 2. It was easy for me to find time to complete my online course(s).

Responses
57 (15% No) and 241 (85% Yes)

Significant Readiness Variables

Readiness Variable	F	P value	Function
Individual Attributes	11.492	.001	.906
Life Factors	9.012	.003	.802

Note: df = 1,296; Function indicates variable importance with Question 2.

Classification Results

Question 2	Predicted Group Membership		Total
	Negative	Positive	
No	2	55	57
Yes	1	240	241

Note: 81% correctly classified

Summary
Findings indicate that *Life Factors and Individual Attributes* were important readiness indicators of whether a student felt it was easy for them to find time to complete their online course. In addition, knowledge of these two readiness indicators showed a 81% classification accuracy. Knowing that 55 students with negative responses were not correctly classified means that other information or variables would be important in determining their situation or response to Question 2.

Question 3. It was easy for me to find a good place to study for my online course(s).

Responses
29 (15% No) and 250 (85% Yes)

Significant Readiness Variables

Readiness Variable	F	P value	Function
Life Factors	10.975	.001	.796
Individual Attributes	10.389	.001	.775
Technical Competency	4.727	.031	.523

Note: df = 1,277; Function indicates variable importance with Question 3.

Classification results

Question 3	Predicted Group Membership		Total
	Negative	Positive	
No	2	27	29
Yes	1	249	250

Note: 81% correctly classified

Summary
Findings indicate that *Life Factors, Individual Attributes, and Technical Competency* were important readiness indicators of whether a student felt it was easy for them to find a good place to study for their online course. In addition, knowledge of these three readiness indicators showed a 90% classification accuracy. Knowing that 27 students with negative responses were not correctly classified means that other information or variables would be important in determining their situation or response to Question 3.

Question 4. It was easy for me to complete my online course(s) with my level of computer skills.

Responses
20 (7% No) and 262 (93% Yes)

Significant Readiness Variables

Readiness Variable	F	P value	Function
Individual Attributes	14.391	.0001	.748
Technical Competency	12.138	.001	.687
Life Factors	10.439	.001	.637

Note: df = 1,280; Function indicates variable importance with Question 4.

Classification results

Question 4	Predicted Group Membership		Total
	Negative	Positive	
No	3	17	20
Yes	3	259	262

Note: 93% correctly classified

Summary
Findings indicate that *Life Factors, Individual Attributes, and Technical Competency* were important readiness indicators of whether a student felt it was easy to complete online course(s) with their level of computer skills. In addition, knowledge of these three readiness indicators showed a 93% classification accuracy. A majority of the students (93%) originally felt they had the computer skills to complete their online course, however, knowing that 17 students with negative responses were not correctly classified means that other information or variables would be important in determining their situation or response to Question 4.

Question 5. Generally speaking, online courses are a good fit for me.
Responses

67 (22% No) and 231 (78% Yes)

Significant Readiness Variables

Readiness Variable	F	P value	Function
Individual Attributes	27.338	.0001	.878
Life Factors	23.890	.0001	.821

Note: df = 1,296; Function indicates variable importance with Question 5.

Classification results

Question 5	Predicted Group Membership		Total
	Negative	Positive	
No	12	55	67
Yes	8	223	231

Note: 79% correctly classified

Summary
Findings indicate that *Life Factors and Individual Attributes* were important readiness indicators of whether a student felt online course(s) were a good fit for them. In addition, knowledge of these readiness indicators showed a 79% classification accuracy. Knowing that 55 students with negative responses were not correctly classified means that other information or variables would be important in determining their situation or response to Question 5.

Question 6. I would take another online course in the future.

Responses
58 (21% No) and 220 (79% Yes)

Significant Readiness Variables

Readiness Variable	F	P value	Function
Individual Attributes	21.988	.0001	.904
Life Factors	15.913	.0001	.769
Technical Knowledge	7.410	.007	.525
Learning Styles	4.382	.037	.404

Note: df = 1,276; Function indicates variable importance with Question 6.

Classification results

Question 6	Predicted Group Membership		Total
	Negative	Positive	
No	7	51	58
Yes	9	211	220

Note: 78% correctly classified

Summary
Findings indicate that *Individual Attributes, Life Factors, Technical Knowledge, and Learning Styles* were important readiness indicators of whether a student will enroll in the future. In addition, knowledge of these readiness indicators shows a 78% classification accuracy. Knowing that 51 students with negative responses were not correctly classified means that other information or variables would be important in determining their situation or response in not desiring to enroll in future courses.

Question 7. If I am having trouble in an online course, I would ask the instructor for help.

Summary

Findings indicated that **no** readiness variables were indicated for classification of negative and positive responses to Question 7. It was surprising, for example, that the Help Seeking readiness variable did not provide any information on students' responses to Question 7.

Summary

The discriminant analysis for Questions 1 to 6 clearly identifies students who had negative responses. More importantly, the students who were misclassified based on the readiness variables that had negative responses can be identified and further follow-up conducted. More than likely, there are a multitude of individual reasons for their dissatisfaction. Moreover, it may not be the same students across all 6 questions, but that could also be determined to indicate the strength of dissatisfaction by a student. A follow-up questionnaire or interview might prove meaningful for university administrators given the importance of student retention.

Structural Equation Modeling

Structural equation modeling permits the identification and use of multiple observed variables to define meaningful constructs or latent variables. This approach permits more reliable and valid analysis of multiple variable relations. A structural equation model (SEM) analysis was conducted for a hypothesized theoretical model to determine if *Ready* would predict *Satisfy*. *Ready* is a latent variable comprised of readiness indicators measured by SmarterMeasure. *Satisfy* is a latent variable comprised of the survey question responses.

Ready, as multiple indicators of readiness to learn online, was defined as:
Life Factors (LF),
Learning Styles (LS),
Individual Attributes (IA),
Technical Knowledge (TK), and
Technical Competency (TC).

Satisfy, as multiple indicators of satisfaction of online learning, was defined as:
Q1. It was easy for me to keep up with the reading required in my online course(s);
Q2. It was easy for me to find time to complete my online course(s);
Q3. It was easy for me to find a good place to study for my online course(s);
Q4. It was easy for me to complete my online course(s) with my level of computer skills;
Q5. Generally speaking, online courses are a good fit for me;
Q6. I would take another online course in the future; and
Q7. If I am having trouble in an online course, I would ask the instructor for help.

Structural Equation and Matrices

Survey Questions
The measurement model for the Y variables that create the latent variable *Satisfy* is shown below.

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \end{bmatrix} = \begin{bmatrix} \lambda_{y_{11}} & & & & & & \\ & \lambda_{y_{22}} & & & & & \\ & & \lambda_{y_{33}} & & & & \\ & & & \lambda_{y_{44}} & & & \\ & & & & \lambda_{y_{55}} & & \\ & & & & & \lambda_{y_{66}} & \\ & & & & & & \lambda_{y_{77}} \end{bmatrix} \eta + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \\ \varepsilon_7 \end{bmatrix}$$

SmarterMeasure Variables

The measurement model for the X variables that create the latent variable *Ready* is shown below.

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} \lambda_{x_{11}} & & & & \\ & \lambda_{x_{22}} & & & \\ & & \lambda_{x_{33}} & & \\ & & & \lambda_{x_{44}} & \\ & & & & \lambda_{x_{55}} \end{bmatrix} \xi + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \end{bmatrix}$$

Structural Equation
The structural equation for *Ready* predicting *Satisfy* is:

$$\eta = \Gamma\xi + \zeta$$

Correlation, Means, and Standard Deviations

Correlation matrix between these multiple indicator variables was:

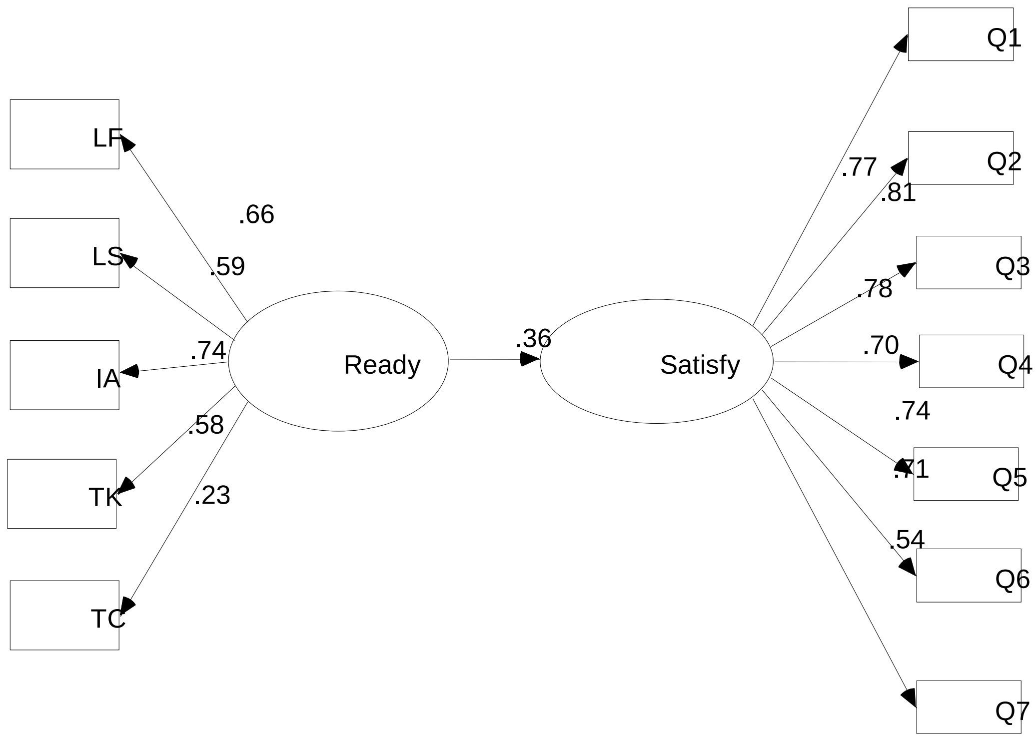
LF	1.000											
LS	.233	1.000										
IA	.420	.434	1.000									
TK	.319	.354	.298	1.000								
TC	.120	.184	.139	.275	1.000							
Q1	.148	.106	.149	.123	**.028**	1.000						
Q2	.126	**.081**	.157	.146	**.036**	.610	1.000					
Q3	.205	.136	.278	.177	.104	.481	.645	1.000				
Q4	.222	.120	.250	.216	.137	.547	.537	.707	1.000			
Q5	.216	.132	.248	.160	**.054**	.589	.615	.542	.487	1.000		
Q6	.209	.148	.246	.192	**.034**	.545	.616	.505	.492	.781	1.000	
Q7	.150	**.066**	.143	**.051**	**-.016**	.426	.421	.484	.499	.322	.369	1.000

Means 83.91 69.10 81.16 74.18 94.06 4.93 4.77 5.21 5.40 4.62 4.82 5.24
Standard Deviation 6.82 12.11 5.58 9.75 8.73 1.65 1.73 1.45 1.39 1.92 1.92 1.55

Note: N = 397 respondents with mean substitution for missing data; Used in the structural equation model (SEM) analysis. Correlation coefficients less than r = +/- .09 are not statistically significant (**boldfaced**).

Figure 1 displays the SEM model for *Ready* predicting *Satisfy.* The indicators of readiness to learn online indicated a significant prediction of the satisfaction questions from the survey. The structural coefficient for *Ready* predicting *Satisfy*, Γ = .36, is statistically significant (z = 6.01, p = .0001). The SEM model is also non-significant (Chi-square = 56.01, df = 41, p = .06, RMSEA = .03), which in SEM analysis implies that the hypothesized SEM model significantly reproduces the covariance (correlation) matrix amongst the variables used in the analysis, i.e. good fit between the hypothesized model and the covariance matrix of variables.

Figure 1. Ready predicting Satisfy



Summary

The set of readiness indicator variables defines a construct or latent variable, *Ready*, which represents a student's readiness to learn (take) online distance education courses. Survey questions were linked to satisfaction of students enrolled in online courses. This set of satisfaction questions defined a construct or latent variable, *Satisfy*. Results indicated that prior to taking online courses, student responses to the readiness variables were important indicators of later student satisfaction/retention. The SEM model analysis indicated *Ready* (which is defined by a set of readiness indicator variables) positively predicts *Satisfy* (which is defined by a set of satisfaction indicator variables). Therefore the multiple SmarterMeasure assessment measures (*Ready*) are a statistically significant positive predictor of the survey responses (*Satisfy*).

Readiness Ranges as a Predictor of Academic Success and Retention

One of the useful features of SmarterMeasure is that school leaders (faculty and/or administrators) can view SmarterMeasure scores through a dashboard which allows them at-a-glance to identify students who might be at risk of not doing well in an online or technology-rich course based on their SmarterMeasure scores. Then based on these findings, the school can provide remediation and support as appropriate. This serves as a valuable student service which can increase the retention rates among online learners. Because the student population of each school is unique, one of the features of SmarterMeasure is that schools can set the grading thresholds (cut points) to determine what level of SmarterMeasure scores should classify their students as "failed," "questionable," or "passed."

Sample University has been using the default settings for the Readiness Ranges cut points. An analysis was conducted to determine if adjusting the Readiness Ranges values (cut points) would increase the predictive nature of the assessment.

An Analysis of Variance was computed using the default cut points and suggested adjusted cut points with GPA, Retention Status, Goodness of Fit, and Length of Discussion Board Postings. The tables below demonstrate the improvements that could be recognized through the adjustment. This analysis demonstrates that the three categorizations provided by the Readiness Ranges can be used as a statistically significant indicator of academic success, retention, engagement, or satisfaction.

Analysis of Readiness Ranges Compared to Academic Success - GPA

	Default Cut Points	Sig.	F	Adjusted Cut Points	Sig.	F	Change Recommended
Individual Attributes	70 / 85	.110	2.213	80 /90	.044	3.155	Yes
Life Factors	70 / 85	.045	2.723	80 / 90	.065	2.435	No
Reading Recall	30 / 65	.046	2.695	70 / 90	.140	1.1832	No
Technical Competency	80 / 90	.390	1.006	90 / 100	.283	1.273	Yes
Technical Knowledge	50 / 75	.071	2.367	70 / 80	.050	2.623	Yes
Typing Rate	21 / 31	.075	2.326	25 / 40	.237	1.419	No

Analysis of Readiness Ranges Compared to Retention Status

	Default Cut Points	Sig.	F	Adjusted Cut Points	Sig.	F	Change Recommended
Individual Attributes	70 / 85	.646	.211	80 /90	.501	.455	Yes
Life Factors	70 / 85	.072	3.272	80 / 90	.006	7.669	Yes
Reading Recall	30 / 65	.547	.364	70 / 90	.776	.081	No
Technical Competency	80 / 90	.213	1.559	90 / 100	.496	.464	No
Technical Knowledge	50 / 75	.914	.012	70 / 80	.295	1.100	Yes
Typing Rate	21 / 31	.038	4.352	25 / 40	.029	4.791	Yes

At Sample University, there is a statistically significant relationship between GPA and whether or not a student was retained. An Independent Samples t-test was computed between GPA groupings and Retention groupings and found a Significance of .004 with an F of 8.242.

Analysis of Readiness Ranges Compared to Satisfaction as Measured by Reported Goodness of Fit

	Default Cut Points	Sig.	F	Adjusted Cut Points	Sig.	F	Change Recommended
Individual Attributes	70 / 85	.000	5.568	80 /90	.101	1.785	No
Life Factors	70 / 85	.005	3.184	80 / 90	.001	4.105	Yes
Reading Recall	30 / 65	.808	.500	70 / 90	.542	.836	Yes
Technical Competency	80 / 90	.382	1.068	90 / 100	.858	.431	No
Technical Knowledge	50 / 75	.117	1.714	70 / 80	.009	2.909	Yes
Typing Rate	21 / 31	.446	.969	25 / 40	.563	.810	No

Analysis of Readiness Ranges Compared to Engagement as Measured by Reported Length of Discussion Board Postings

	Default Cut Points	Sig.	F	Adjusted Cut Points	Sig.	F	Change Recommended
Individual Attributes	70 / 85	.021	2.207	80 /90	.286	1.213	No
Life Factors	70 / 85	.022	2.204	80 / 90	.065	1.816	No
Reading Recall	30 / 65	.072	1.771	70 / 90	.062	1.828	Yes
Technical Competency	80 / 90	.884	.486	90 / 100	.779	.621	Yes
Technical Knowledge	50 / 75	.210	1.350	70 / 80	.500	.929	No
Typing Rate	21 / 31	.609	.808	25 / 40	.215	1.339	Yes

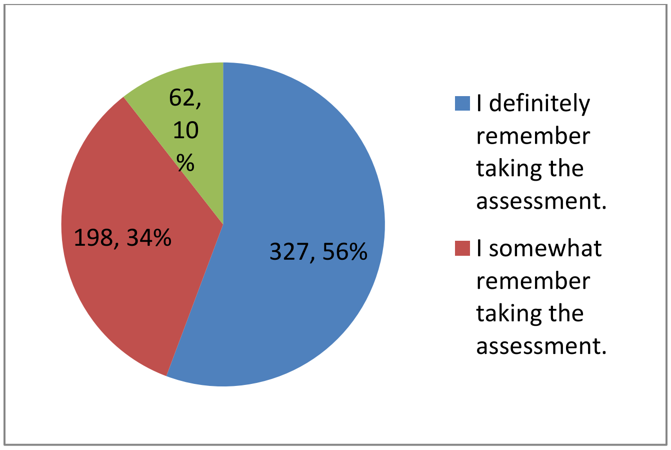
This analysis provided a balanced finding that changing the Readiness Ranges to be a better predictor of one of the four constructs (academic success, retention, engagement, or satisfaction) could have an opposite impact on the predictive nature of one or more of the other four constructs.

Satisfaction with the SmarterMeasure Assessment

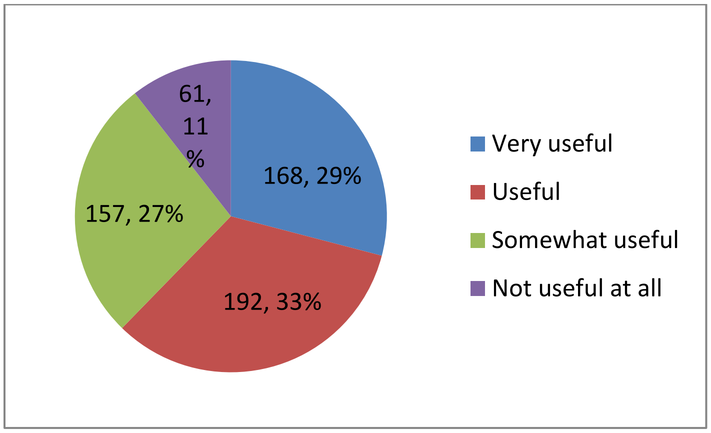
Some of the students who were invited to participate in the survey would have recently taken the SmarterMeasure assessment. Others could have taken the assessment as long as two years ago. To determine the degree to which students remembered the assessment as well as the degree to which they considered it a useful student service, the following questions were asked on the survey:

How well do you remember taking the READI assessment?
How useful was the assessment as a student service?

The majority of survey participants (90%) either somewhat or definitely remembered taking the assessment.



The majority of survey participants (89%) found the assessment somewhat useful, useful, or very useful while only 11% did not find it useful at all as a student service. When the data set was filtered to remove those who did not remember the assessment at all, then the percentage of students who rated the assessment as "Not useful at all" dropped to 9%.



APPENDIX

SmarterMeasure Scales and Sub-Scales

Scale	Sub-scales	Items
Individual Attributes	Procrastination Time management Persistence Willingness to ask for help Academic attributes Locus of control	24
Life Factors	Availability of time to study Availability of a dedicated place to study Reason for continuing one's education Support resources from family, friends, and employers Perception of academic skills	20
Learning Styles	Identifies the degree to which they posses each of the following learning styles: Visual Verbal Social Solitary Physical Aural Logical	35
Reading Skills	Reading rate On-screen reading recall	11
Technical Knowledge	Technology usage Technology in your life Technology vocabulary Personal computer/Internet specifications	23
Technical Competency	Computer competency Internet competency	10
Typing Skills	Typing rate Typing accuracy	1

Survey Results – Frequencies, Response Rates, Means, and Standard Deviations

	N Valid	Missing	Mean	Std. Deviation
Learning Styles	372	25	69.09	12.514
Individual Attributes	376	21	81.15	5.73
Reading Rate	371	26	226.16	231.70
Typing Accuracy	356	41	94.05	13.86
Typing Rate	356	41	28.04	11.85
Technical Knowledge	357	40	74.17	10.28
Life Factors	299	98	83.91	7.86
GPA	397	0	2.74	.923
Number of Courses per Term	397	0	2.95	1.23
Required Reading	397	0	4.93	1.65
Find Time	396	1	4.77	1.73
Good Place	393	4	5.21	1.45
Computer Skills	397	0	5.40	1.39
Good Fit	397	0	4.62	1.92
Take Another	394	3	4.82	1.92
Ask for Help	390	7	5.24	1.56
Hours per Week	397	0	6.13	2.71
Logins per Week	397	0	5.87	2.67
Length of Posting	391	6	6.55	2.77
Use Tech Support	295	102	1.99	1.91
Remember READI	397	0	1.49	.65
How Useful	390	7	1.80	.98

	Strongly Disagree		Moderately Disagree		Slightly Disagree		Neutral		Slightly Agree		Moderately Agree		Strongly Agree	
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Required Reading	8	2.0%	7	1.8%	14	3.5%	24	6.0%	33	8.3%	106	26.7%	205	51.6%
Find Time	10	2.5%	15	3.8%	15	3.8%	25	6.3%	42	10.6%	99	24.9%	190	47.9%
Good Place	5	1.3%	6	1.5%	8	2.0%	16	4.0%	32	8.1%	79	19.9%	247	62.2%
Computer Skills	7	1.8%	6	1.5%	1	.3%	14	3.5%	16	4.0%	61	15.4%	292	73.6%
Good Fit	18	4.5%	15	3.8%	17	4.3%	32	8.1%	35	8.8%	86	21.7%	194	48.9%
Take Another	21	5.3%	11	2.8%	13	3.3%	29	7.3%	20	5.0%	63	15.9%	237	59.7%
Ask for Help	6	1.5%	5	1.3%	3	.8%	21	5.3%	26	6.5%	59	14.9%	270	68.0%

	Hours per Week		Logins per Week		Posting Length		Contact Tech Support	
	N	%	N	%	N	%	N	%
1	17	4.3%	14	3.5%	11	2.8%	181	61.4%
2	18	4.5%	19	4.8%	14	3.6%	57	19.3%
3	32	8.1%	38	9.6%	28	7.2%	23	7.8%
4	59	14.9%	74	18.6%	48	12.3%	9	3.1%
5	62	15.6%	71	17.9%	68	17.4%	5	1.7%
6	39	9.8%	37	9.3%	47	12.0%	4	1.4%
7	29	7.3%	29	7.3%	23	5.9%	4	1.4%
8	48	12.1%	26	6.5%	25	6.4%	3	1.0%
9	12	3.0%	11	2.8%	6	1.5%	4	1.4%
10	81	20.4%	78	19.6%	121	30.9%	5	1.7%

How well do you remember taking the READI assessment?	Frequency	Percent
I definitely remember taking the assessment.	228	57.4
I somewhat remember taking the assessment.	134	33.8
I do not remember it at all.	35	8.8

How useful was the assessment as a student service?	Frequency	Percent
Not useful at all	48	12.1
Somewhat useful	92	23.2
Useful	139	35.0
Very useful	111	28.0

School Status	Frequency	Percent
Active	228	57.4
Dismissal	3	0.8
Externship	13	3.3
Graduate	52	13.1
Leave of Absence	5	1.3
NDS - Active	1	0.3
NDS - Fulfilled	1	0.3
Original Enrollment	4	1
Pending Graduate	2	0.5

Probation	9	2.3
Standard Period of Non-Enrollment	1	0.3
Transfer to Other Campus	1	0.3
Transfer to Other Program	44	11.1
Withdraw	33	8.3
Total	397	100

Grades	Frequency	Percent
	42	10.6
A	196	49.4
A-	7	1.8
B	80	20.2
B-	2	.5
B+	2	.5
C	28	7.1
C-	3	.8
C+	2	.5
D	2	.5
F	19	4.8
NC	1	.3
PD	13	3.3
Total	397	100.0

Number of Courses per Term	Frequency	Percent
1	41	10.3
2	99	24.9
3	154	38.8
4	72	18.1
5	8	2.0
6	18	4.5
7	5	1.3
Total	397	100.0

GPA Groupings	Frequency	Percent
D	31	7.8
C	89	22.4
B	211	53.1
A	66	16.6
Total	397	100.0

Epilogue - Making a Difference for Students

Thermometer analogy

As a parent, I may observe my child to be playing lethargically and looking flush. I suspect that they may be getting sick, so I use a thermometer to take their temperature. If my child has a fever, then I have a decision to make. Should I give them some over-the-counter medicine or take them to the doctor? That decision may largely depend on the measurement of their temperature. If it is 100 degrees, I may just give them some over-the-counter medicine. But if their temperature is 105, then I may decide to take them to the doctor. That night as I reflect on the day and my role as a parent, should I feel good about the fact that I took my child's temperature? Yes, but what I should really feel good about is the fact that I used that measurement of temperature to inform a decision that prompted action.

SmarterMeasure is similar to a thermometer in that it provides a measurement of the learner's level of readiness for studying in an online or technology-rich environment. It is a rather sophisticated thermometer in that it gives multiple points of measurement, but nonetheless it is still just a measurement. While there are some benefits of providing the results of the measurement to the students, the real benefit of SmarterMeasure comes when schools look at the student's scores and then take appropriate action.

The research strategies in this project are parallel to computing correlations between a child's temperature and then some measure of their health. There would be benefit in doing that, but the real benefit would be in identifying life habits that impact the child's health and focusing on reinforcing those habits. So while the intention of these research strategies is to determine the relationship between SmarterMeasure scores and metrics of student success and satisfaction, we really encourage SAMPLE UNIVERSITY to engage in a dialogue with us about implementing integration strategies that impact student success.