Do Online Readiness Surveys do What They Claim?
Validity, Reliability, and Subsequent Student Enrollment Decisions

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ABSTRACT

Online readiness surveys are commonly administered to students who wish to enroll in online courses in college. However, there have been no well-controlled studies to confirm whether these instruments predict online outcomes specifically (as opposed to predicting course outcomes more generally). This study used a sample of 24,006 students to test the validity and reliability of an online readiness survey similar to those used in practice at a majority of U.S. colleges. Multilevel models were used to determine if it was a valid predictor of differential online versus face-to-face course outcomes while controlling for unobserved heterogeneity among courses taken by the same student. Student self-selection into online courses was also controlled using student-level covariates. The study also tested the extent to which survey score correlated with subsequent decisions to enroll in an online course. No aspect of the survey was a significant predictor of differential online versus face-to-face performance. In fact, student characteristics commonly collected by institutional research departments were better predictors of differential online versus face-to-face course outcomes than the survey. Furthermore, survey score was inversely related to subsequent online enrollment rates, suggesting that the use of online readiness surveys may discourage some students from enrolling in online courses even when they are not at elevated risk online. This suggests that institutions should be extremely cautious about implementing online readiness surveys before they have been rigorously tested for validity in predicting differential online versus face-to-face outcomes.

Keywords: online readiness survey; online learning; retention; predictive validity; reliability

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INTRODUCTION

A majority of students now take at least one college course online, and community college students enroll in online courses at particularly high rates (Allen & Seaman, 2013; Community College Research Center (CCRC), 2013). While a number of studies and meta-analyses have established that students can learn as much online as they do in a face-to-face format (see e.g. Bernard et al., 2004), students also seem to drop out of online courses at higher rates (see e.g. Nora & Snyder, 2009; Patterson & McFadden, 2009). Because of the higher rates of attrition in online courses, the majority of community colleges in the United States now use online readiness surveys to screen students who are interested in enrolling online (Liu, Gomez, Khan, & Yen, 2007), with the result that these surveys are used to give millions of students feedback on their suitability to take an online course. However, to date, no well-controlled studies have evaluated how well these surveys actually predict *differential* performance in online versus face-to-face courses, or what effect the administration of such surveys has on subsequent student decisions to enroll in online courses. If online readiness surveys are not accurately identifying which students are at higher risk in the online environment, then community colleges across the United States are wasting valuable resources administering invalid instruments. Furthermore, it is possible that negative survey feedback is discouraging many students from enrolling in online courses even when they are likely to successfully complete courses in the online environment. Since it is not known whether such students enroll in alternative face-to-face courses after being discouraged from enrolling online, the use of invalid screening instruments may actually be decreasing student momentum in college and thereby inhibiting college persistence and degree attainment.

This study seeks to analyze the reliability and validity of one particular online readiness

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survey that was a mandatory prerequisite for all students interested in enrolling in any online course at a large community college in the Northeastern United States. We examine the predictive validity of this survey in identifying *differential* online versus face-to-face performance. We subsequently analyze the relationship between a student's survey score and their likelihood of subsequent online course enrollment to determine the extent to which students with lower survey scores seem to subsequently enroll in online courses at lower rates. The online readiness survey analyzed in this study was chosen because it seems to be a good representation of the online readiness surveys currently used in practice at a majority of U.S. community colleges (and not because it is the ideal instrument for measuring student online readiness). The intent of this study was not to develop and test the most ideal and theoretically sound online readiness instrument; rather, its aim was to analyze the extent to which online readiness surveys, as they are currently implemented in practice at the vast majority of institutions, do what they are intended to do, and to what extent this current implementation may have unintended negative consequences.

The particular strengths of this study are its large size (n=24,006), the diversity of the sample (83% non-white race/ethnicity, 70% female, 42% 24 years old or older, 29% enrolled part-time, and 43% Pell grant recipients), and the fact that the survey was administered to all students in the population of interest at this particular college during the year-long study period, thereby minimizing coverage, sampling, and non-response error to an extent that is typically not possible in survey research.

BACKGROUND

Theory and Prior Research

Online Learning, Attrition, and the Motivation Behind the Use of Online Readiness Surveys

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Online learning is rapidly becoming a significant component of higher education in the United States, with online enrollments increasing much faster than higher education enrollments more generally (Allen & Seaman, 2010; Allen & Seaman, 2013; Community College Research Center (CCRC), 2013; Howell, Williams, & Lindsay, 2003). Online courses are often seen as a way to increase college access for non-traditional students (Picciano, Seaman, & Allen, 2010); however, whether online offerings actually increase college enrollment or persistence is unclear (Jaggars, 2011). The research evidence suggests that students can learn just as much online as they do in traditional face-to-face classes; many studies and meta-analyses suggest no positive or negative effect of the online environment on learning outcomes as measured by exams or course grades (Bernard et al., 2004; Bowen & Lack, 2012; Bowen, Chingos, Lack, & Nygren, 2012; Jaggars, 2011). This suggests that online courses can provide improved access to higher education, particularly for non-traditional students, without compromising learning outcomes. However, online courses have dropout rates that are 7-20 percentage points higher than those in face-to-face courses (Carr, 2000; Hachey, Wladis, & Conway, 2012; Moody, 2004; Morris & Finnegan, 2009; Nora & Snyder, 2009; Patterson & McFadden, 2009; Smith & Ferguson, 2005), and a few studies have connected online course-taking to overall academic non-success in college (Jaggars & Xu, 2010; Xu & Jaggars, 2011). Because of higher attrition concerns, many colleges would like to identify the students at highest risk of dropping out in the online environment before they enroll.

Prevalence of Online Readiness Surveys in Practice

One widely-used technique to filter out students who may be "at-risk" in the online environment is the use of online readiness surveys (Liu, Gomez, Khan, & Yen, 2007), which can range from tests of basic software proficiency (e.g. Northwest Arkansas CC) to more

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comprehensive assessments including questions on lifestyle, goals and learning styles (e.g. University of Georgia). A literature search revealed two surveys of online readiness surveys used by U.S. institutions and suggests that the use of these surveys has become more prevalent over the last decade. The first (Kerr, Rynearson, & Kerr, 2006) was conducted in 2002, and included high schools and various higher education institutions which were chosen randomly from an Internet search for online programs. This study found that 60% of institutions used online readiness surveys, and that the six major underlying constructs of those surveys were: computer skills, time management, motivation, academic skills (reading and writing), the need for online delivery, and learning skills. In the second study (Liu et al., 2007), community colleges in the top 10 most populated metropolitan areas in the U.S. and an additional random sample of 20 community colleges from Maryland and Virginia were evaluated. All 30 institutions in the sample used an online readiness assessment. Survey constructs identified were: motivation, learning style, self-efficacy, persistence, computer literacy, technology usage, communication skills, learning styles, and other student characteristics. However, these categories were chosen without a formal analysis of content validity (such as factor analysis) by the study authors. It is not clear the degree to which these two studies are nationally representative, or the degree to which the survey constructs identified are valid. Nonetheless, these two surveys do highlight the extremely high prevalence of online readiness surveys as screening tools for online college courses, and the fact that the use of these surveys seems to be increasing over time.

Construct Validity, Internal Consistency, and Constructs Measured

Construct validity and internal consistency have been demonstrated for a number of different online learning readiness instruments in the education literature. Twelve instruments were tested for construct validity using factor analysis: the Motivated Strategies for Learning Questionnaire

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(MSLQ), developed and tested by Pintrich, Smith & Garcia(1993); the Bartlett-Kotrlik Inventory of Self-Learning (BISL), developed and tested by Bartlett & Kotrlik (Bartlett & Kotrlik, 1999); SmarterMeasure (formerly Readiness for Education At a Distance Indicator [READI]), developed by SmarterMeasure (Elam, 2012; SmarterMeasure, 2013) and tested by Hukle (2009); the Self-Directed Learning Readiness Scale (SDLR) developed and tested by Fisher, King & Tague (2001); the Management Education by Internet Readiness (MEBIR) scale, developed and tested by Parnell & Carraher (2003; 2005); the Test Of Online Learning Success (TOOLS), developed and tested by Kerr, Rynearson & Kerr (Kerr et al., 2006); the Tertiary Students' Readiness for Online Learning (TSROL) developed and tested by Pillay, Irving, & Tones (Pillay, Irving, & Tones, 2007); a survey developed and tested by Dray, Lowenthal, Miszkiewicz, Ruiz-Primo & Marczynski (2011); the Readiness for Online Learning questionnaire (ROL), developed and revised by McVay (2001) and tested by (Bernard, Brauer, Abrami, & Surkes, 2004); the Online Learning Readiness Scale (OLRS) (Hung, Chou, Chen, & Own, 2010); a survey developed and tested by Watkins, Leigh, & Triner (2004). Throughout the studies cited in this paragraph, the first eleven demonstrated construct validity, and the first eight also had their reliability tested and confirmed. Several other surveys which have been explored in the literature were not tested for construct validity or reliability (Cross, 2008; Hall, 2008; Maki & Maki, 2003; Waschull, 2001). Some studies have also assessed test-retest reliability (Kerr et al., 2006), criterion validity (Kerr et al., 2006), content validity (2001), convergent validity (2003; 2005), and discriminant validity (2003; 2005). The validated constructs generally fall into the following categories: self-direction/management/control, motivation, beliefs, cognitive strategies, technical competence (e.g. skills, access, self-efficacy), and preference for e-learning format. A summary of the constructs measured in the online readiness surveys can be found in *Table 1*.

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Do Online Readiness Surveys do What They Claim?

General predictive validity

There are a number of studies in the research literature that aimed to test the validity of these instruments in predicting academic outcomes for students enrolled in online courses.

Puzziferro (2008) tested the predictive validity of the MSLQ instrument on 815 students enrolled in online liberal arts classes at a community college. This study found that time management and study self-regulation were significantly related to course success but that rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, peer learning, and help seeking were not.

Aragon & Johnson (2008) compared the characteristics of online course completers and non-completers using the BISL instrument. They also collected basic demographic information. Completers were more likely female, enrolled in more classes, with a higher G.P.A., but there was no significant difference regarding academic readiness or self-directed learning.

DeTure (2004) tested the OTSES instrument in addition to another instrument intended to test field dependence/independence on 73 community college students enrolled in online classes and determined that there was no significant correlation of scores on either survey construct with final course grade.

Two studies tested the predictive validity of the SmarterMeasure/READI instrument. Hukle (2009) tested the survey on a random sample of 250 community college students enrolled in an online course, taken from a larger sample of students who volunteered to take the readiness survey online, and found that Verbal Learning Style correlated significantly to online course completion. Fair & Wickersham (2012) tested the survey on 194 students enrolled in a basic communication class at a community college, but none of the constructs measured by the survey were correlated with final course grade.

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Chou & Chen (2008) give an overview of predictive validity studies of the SDLR instrument, describing five studies which took place in the U.S. or in Taiwan. No conclusion could be drawn about the correlation between survey score and course outcome because only one of the five studies showed a significant relationship, and the other studies had very small sample sizes. Mead (2011) tested the instrument on 216 students enrolled in online courses at a Midwestern university in the U.S. and found a modest correlation between self-directed learning readiness (as measured by the SDLR) and actual course grade. Shokar, Shokar, Romero, & Bulik (2002) noted that the SDLR also predicts outcomes in face-to-face classes.

Bernard, Brauer, Abrami, & Surkes (2004) tested the revised McVay readiness survey on 167 Canadian undergraduates enrolled in online courses and found that self-direction and beliefs were significant positive predictors of online course grade, explaining 8% of the variance, but that G.P.A. was a much stronger predictor of online course outcome than the survey. Hall (2011) also tested the revised McVay instrument in a study on 31 online and 116 face-to-face community college students and found that the survey score was a borderline significant predictor of online course grade (for $\alpha=0.05$), and not significant for face-to-face. It explained 10% of the variance in final course grade, which was much less than the proportion of variance explained by the student's major. The interaction between survey score and online medium in predicting course grade was not tested, so it is unclear whether the instrument predicted online course outcomes specifically, even though both online and face-to-face students were included in the sample.

Waschull (2005) created a questionnaire which was not analyzed for validity or reliability, and tested it on 57 online psychology students at a technical college in the U.S. Out of 4 factors, only self-discipline/motivation was significantly correlated with course grades, and the author

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concluded that the same factors may predict success in both online and face-to-face classes. Kerr, Rynearson & Kerr (2006) tested the TOOLS instrument on 56 undergraduate and graduate students in online courses at a public university in the U.S. and found that in a regression analysis, only academic skills was a significant predictor of online course grades, explaining 9% of variance in outcomes.

Cross (2008) developed a survey but did not test it for construct validity or reliability, and gave it to 242 community college students enrolled in online classes. Neither total score no individual subscales were significant predictors of online course dropout at 4, 7, or 10 weeks. Yukselturk & Bulut (2007) administered a demographic survey, an internal-external locus of control scale, a learning style inventory, and a questionnaire on motivated strategies for learning to 80 undergraduate and graduate students in an online certificate program in Turkey. Success was not clearly defined, but was based in some way on outcomes on course assignments and the final exam. In regression analysis, only self-regulation was a significant predictor of online course success, explaining 16.4% of the variation.

Hall (2008) administered a survey based on two instruments used at two different community colleges to 83 online and 228 face-to-face community college students. Survey score was not a significant predictor of course withdrawal. It was a significant predictor of online but not face-to-face course grade, explaining 8% of the variation in online course grade, which was less than the proportion of variation explained by the subject of the course. The interaction between survey score and online medium in predicting course grade was not tested.

A number of these studies showed no correlation between survey score and online course grade or retention. For those that did show a correlation, different factors were identified as significant: e.g. self-direction, beliefs, motivation, and academic skills. However, these factors

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may simply be predictors of grades in *any* course and may not be specific to the online medium at all, because none of these studies properly tested the interaction between these factors and the online medium in predicting course grade. Moreover, three of these studies (Bernard et al., 2004; Hall, 2008; Hall, 2011) identify factors other than survey instruments which were significantly better predictors: G.P.A., course subject, and declared major. So even if some online readiness surveys could be shown to predict online course outcomes, the demographic and academic information routinely collected by college institutional research departments may serve as a better predictor of online outcomes than survey instruments, and would be cheaper and easier to use than surveys.

Predictive validity for the online environment specifically

The purported objective of online readiness surveys is to identify those students who are not well-suited to the online environment specifically[1]. The purpose of these surveys is not, for example, to simply identify students who might be at risk of failing or dropping out of *any* college class more generally, whether that class is offered online or face-to-face. Therefore, in order to determine if an online readiness survey is serving its purpose, one should investigate whether the survey can identify those students who are likely to do significantly worse online than would be expected based on their face-to-face performance. This is different than simply testing whether or not the survey constructs correlate with high course grades or high rates of course persistence: if survey constructs do correlate with course outcomes, it may simply be because those constructs are good predictors of academic outcomes more generally, and there

[1] It is possible that there are other reasons for administering such surveys (e.g. to education students about what is required to succeed in an online course), but a systematic look at the focus of the research literature on this topic, discussions among administrators at conferences and other meetings regarding these surveys, the marketing approach of companies that sell surveys such as these to colleges, and the website text on college websites where these surveys are used, tend to support the interpretation that much of their use is motivated by a desire to differentiate which students are "at-risk" versus those who are "well-suited" to in online courses.

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may be no correlation with those constructs and learner suitability for the *online* environment specifically. For example, just because G.P.A. correlates with online course outcomes doesn't mean that higher G.P.A. students are better suited to the online environment than those students with lower G.P.A.'s. Rather, we would expect a student with a high G.P.A. to do well in any course, whether it were offered online or face-to-face.

This is an important distinction that uncovers the major weakness of almost all existing studies in the research literature that test the predictive validity of online readiness surveys. Each of the above studies aimed to test the predictive validity of online readiness surveys, but none of them tested the *interaction* between online readiness constructs or score and the course medium, and thus none of these studies yields results that can be used to draw conclusions about which students are at risk in the online environment specifically.

In our search of the research literature, we could only find one study that attempted to analyze the interaction between survey constructs and the course medium. Maki & Maki (2003) tested two sets of surveys along with some control variables for instructor and class cohort. They compared students in hybrid[2] versus face-to-face sections of an introductory psychology class (341 students in the first study and 344 students in the second study). Students self-selected into the hybrid versus face-to-face sections. They analyzed how survey scores related to examination scores, scores on specific content questions, and student satisfaction in the course. For the first study, scores on content questions at the beginning of the course, academic major, and year in college (e.g. freshman) were used as control variables. There was no significant interaction

[2] Later in the methods section of this paper we define what a hybrid course is for the data used in this analysis; however, throughout the literature review, we used the term hybrid based on the terminology used by the papers that we cite; different papers use different definitions of hybrid courses, and many use the term hybrid without giving a precise definition of what constitutes a hybrid versus a fully online or face-to-face course. In general, a hybrid course is a course in which some part of the content is delivered online and some part is delivered face-to-face, but there may be large variation in terms of the actual percentage of content delivered online.

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between the course medium and instructor, major, year in college, or the five personality characteristics tested by the survey, in predicting either examination scores or performance on specific content questions. For the second study, the only significant interactions with course medium were instructor, and the student's response to a five-point Likert scale of agreement with the statement "I enjoy class discussions" in predicting examination scores. In the hybrid courses, students who reported enjoying class discussion more did significantly worse than those who reported enjoying it less, while the opposite pattern was true (but nonsignificant) in the face-to-face sections. However, because students self-selected into the hybrid versus face-to-face course medium and the study did not employ controls for student characteristics that tend to correlate with online enrollment, it is unclear how these results can be interpreted. It may be that any significant interactions (or lack thereof) with course medium in this study are an artifact of the fact that students who choose to enroll in online classes tend to have very different characteristics than students who take only face-to-face courses (Wladis, Conway, & Hachey, n.d.).

This study seeks to rectify this gap in the research literature by testing the extent to which an online readiness survey, which contains many of the constructs commonly identified in the research literature and commonly used by colleges in practice, can identify students who are likely to do significantly more poorly in an online course than would be expected given their face-to-face performance. This will be done by testing the interaction between score on an online readiness survey (or individual survey constructs) with the course medium in predicting successful course completion, while also controlling for individual student characteristics that might affect self-selection into online courses.

PURPOSE OF THE STUDY

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Do Online Readiness Surveys do What They Claim?

The purpose of this study was to assess the extent to which a "typical" online readiness survey, as implemented in practice, accurately identifies students who are "at-risk" in the online environment specifically, and to explore the extent to which a student's score on the survey correlates with their subsequent decision to enroll online. Specifically, this study has three aims:

1. To explore the factor structure and reliability of an online readiness survey instrument that is currently in use at a large urban community college in the U.S., one which specifically appears to test several of the more common e-learning readiness survey constructs and generally appears to resemble instruments currently in use at many U.S. community colleges.
2. To test the predictive validity of this survey in determining a student's likelihood of doing significantly worse online than expected given their performance in face-to-face courses, while rigorously controlling for student-level factors that might affect self-selection into online courses or course performance more generally .
3. To determine whether a student's online readiness survey score correlates with their decision to subsequently enroll in an online course.

METHODOLOGY

Data source and sample

The population of interest in this study is the group of those students who consider registering for an online course in college. Online readiness surveys are typically administered to students who are thinking about enrolling in online courses (they are not typically given to students at the college who have no interest in enrolling online), and the purpose of these surveys is to predict, for this population, whether or not a particular student is at a higher risk of failing

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or dropping out in the online environment than would be expected given their face-to-face performance.

This study uses a dataset of 24,006 students, consisting of all students at a large urban community college in the Northeast who expressed interest in taking an online course in 2011 by clicking through a set of instructions explaining how to register for a specific online class at the college and then completing the online readiness survey on the website. Completion of this survey is a required pre-requisite at the college for all students before they can register for their first online course.

A community college was chosen as the focus of this study for a number of reasons. Community colleges have more online course offerings than other higher education institutions, and most college students at some point take courses at a community college: about about 53% of all college freshmen (U.S. Census Bureau, 2012) are currently enrolled at a public two-year college In addition, community colleges also have higher concentrations of students who have traditionally been underrepresented in higher education and students who are at higher risk of college dropout: they have higher percentages of minorities, women, students with disabilities, first-generation college students, students who live below the poverty line, and students who require developmental coursework (Goan & Cunningham, 2007; Goldrick-Rab, 2006; U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2009).

The college which is the focus of this study enrolls roughly 25,000 students annually in degree-programs, with an additional 10,000 per year in continuing education programs. Eight-eight percent of the students are non-white minorities; over half are first-generation college students, and 89% are eligible for state tuition-assistance. The college has been designated as

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both an Hispanic serving institution and a Minority serving institution by the U.S. Department of Education. Credit-bearing online courses were first offered at the college in 2002, and the college now offers more than 125 online courses each semester. The college offers online courses in all areas, including liberal arts and career courses, lower and upper level courses, elective and required courses, and courses in the humanities, social sciences, and STEM fields.

Individual courses are selected to be developed for the online medium by individual professors who already teach them face-to-face, contingent upon approval by the department chair and the college provost. Faculty then undergo one semester of training in the college's e-Learning center while they develop their online course; final online courses are then approved by the department chair, personnel at the e-Learning center, and the college Dean for Academic Programs and Instruction, using a metric developed by e-Learning faculty and support personnel, based on Sloan Consortium recommendations. Every course offered online is also offered face-to-face at the college, and instructors typically teach the course for several semesters face-to-face before they develop the course to be taught online. In particular, instructors typically continue to teach the same course both online and face-to-face after developing a course for the online medium.

Roughly 12% of the course offerings are currently online. Online courses are indistinguishable from face-to-face courses on the student's transcript, and students register for online courses in the same manner as for face-to-face courses, with the exception of the required online readiness survey, which must be taken online before a student can enroll in an online course for the first time at the college.

Initially, 24,227 survey responses were obtained. After the removal of duplicate survey submissions and submissions where the student name and ID combination could not be clearly

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identified, 24,006 responses remained. Student survey responses were matched to institutional records, and student information was obtained on the following factors: ethnicity, gender, age, full-time versus part-time enrollment, G.P.A. (grade point average), academic major, zip code, financial aid information about whether the student received Pell grants or federal TANF (temporary assistance for needy families) benefits ("welfare"), and information on all classes which the student took at the college during the 2011 calendar year. Note that, after taking the survey, a student may or may not have chosen to enroll in an online class.

The Survey Instrument

The e-learning readiness survey used in this study is one that has been implemented for several years at a large urban community college in the Northeastern U.S. It was initially developed by faculty and staff in the college's e-learning center, based on instruments used at other colleges and those identified in the research literature, and e-learning staff and faculty assessed each of the items for content validity. Every student who wishes to enroll in an online course at the college must take the survey before registering for an online course for the first time, and the college operates with a policy of open access. For these two reasons, the college wanted the survey to be short with the intention that it could be completed quickly and that taking the survey did not serve as a significant barrier to class registration. Once a student takes the survey for the first time, they are cleared to register for online courses at any future semester at the college (regardless of their score), and students are then able to register for an online course in the same way they would register for any face-to-face course at the college. The survey consists of twelve questions which address areas such as academic preparation/skills, learning style, computer access/experience, and time management and initiative. The exact survey questions can be seen in the *Appendix*.

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Online readiness survey questions on this instrument are scored on a scale of 1-4, with the answers in order from highest value (4) to lowest value (1), with the exception of questions 1,7, and 8, which were reverse coded to inhibit response pattern bias. Student scores can therefore range from 12 to 48 on the survey. After taking the survey, students are presented with feedback on their score which advises them about whether an online course is likely a good fit for them, and if their score is lower, they are advised on what steps they might want to take to better prepare themselves before taking an online course. In addition, all students (regardless of survey score) are prompted to read a short set of statements about expectations in an online course, and indicate (through the click of a radio box online) that they have understood these expectations. Because students can only submit the survey if it is complete, there was no missing data in the survey responses.

In order to assess the representativeness of this particular online survey instrument in comparison to actual practice at community colleges in the U.S., we conducted a random sampling of community colleges in the Integrated Postsecondary Education Data System (IPEDS), which is a dataset maintained by the U.S. Department of Education that collects information annually from every college in the U.S. that participates in federal student financial aid programs. Fifty community colleges were selected from IPEDS using a random number generator to rank all the colleges in the database. For each of these fifty colleges, information was collected about the college's online program and its use of online readiness surveys. Overall, 75% of students attending colleges in the sample were at an institution that used online readiness surveys. Of the online readiness surveys used by colleges in this sample, the median number of questions on the surveys was 15, and 73% of the surveys had 20 or fewer questions. A review of the specific questions used on these surveys revealed a distribution of question types

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that was similar in most cases to that used on the online readiness survey used in this study, with a number of colleges using questions that were almost identical in wording to the questions used in the study survey.

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Measures

The dependent variable for the predictive validity part of this study was whether a student successfully completed the course (online or face-to-face) with a grade of "C-" or higher. This standard was chosen because it is the minimum grade required for a student to obtain credit for the course in their major, or for them to receive transfer credit in the university system in this study. We use successful course completion as a measure rather than retention, because retention measures don't distinguish between students who receive "D" and "F" grades and those who withdraw, even though the effective outcome of the course in which these grades were received for most of these students (in terms of credit toward degree and successful academic progress) is similar. All courses in which a student enrolled in the year after they took the online readiness survey were included in the analysis. Courses in which students received an incomplete or pending grade were excluded from the analysis.

The independent variables included: ethnicity, gender, age, full-time versus part-time enrollment, G.P.A., a student's reason for taking the course (to fulfill elective, distributional or major requirements), the median household income of the student's zip code, whether the student received a Pell grant, whether the student received federal TANF benefits ("welfare"), and whether the specific course taken was online or face-to-face.

Course delivery method was categorized as online if it was either hybrid or fully online. Fully online courses are those courses for which more than 80% of the class time is spent online, and hybrid courses are those courses in which 30-80% of the class time is spent online. These definitions are those used by the college in this study, and are taken from the Sloan Consortium definitions (Allen & Seaman, 2010). (In practice, fully online courses at the college are conducted entirely online, with at most a few face-to-face meetings for orientation or testing in

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some cases, and hybrid courses typically meet once every 1-2 weeks.) Two analyses were run: one in which online courses were compared to face-to-face courses, and one in which course medium was broken down into three categories: face-to-face, hybrid, and fully online.

G.P.A. was measured as a student's G.P.A. at the beginning of the semester in which they enrolled in the course that was a part of the study sample; students who were first-time freshmen (roughly 10% of the sample) had no G.P.A., but were coded as first-time freshmen by labeling them as a separate G.P.A. category "none". G.P.A. was treated as a categorical variable, with categories chosen to match the letter grade categories: A, B, C and D/F.

There were three separate measures of socio-economic status (SES) used in this study: whether the student received federal TANF benefits ("welfare"); whether the student received federal Pell grant monies; and the average household income of the student's zip code. TANF and Pell grant status were combined for use as a single independent categorical variable with four values: the student applied for financial aid but received neither Pell grants nor federal TANF benefits ("none"); the student received a Pell grant (but no federal TANF benefits); the student received both a Pell grant and federal TANF benefits; or the student did not apply for financial aid. Those students who did not apply for financial aid were treated as a separate group, because we suspect that this group has unique characteristics: for example, students with relatively high incomes often do not apply for financial aid because they do not expect to qualify, or students who enroll in college at the last minute do not apply because they have missed the deadlines; foreign students also do not typically apply for financial aid because they do not qualify.

The median household income of a student's zip code as obtained from the U.S. Census Bureau's American Community Survey as administered in 2011, and was also used as a measure

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of SES in this study. Because this study was conducted in a high density urban environment, the geographic area covered by each zip code represented quite a small geographic unit: in some cases denoting a single high-rise building, with the average zip code in the area covering roughly 0.40 square miles. Neighborhood SES has been shown to be a significant predictor of differences above and beyond individual household income (see e.g. (Owens, 2010).

Student age was also used as an independent variable. Rather than treat age as a continuous variable, we group students into two age categories: under 24; and 24 and above. The reason for this grouping is that before or after 24 years is the age typically cited in the higher education retention literature as denoting delayed enrollment (U.S. Department of Education, Institute of Education Sciences, National Center for Education Statistics, 2002). We also include ethnicity and gender as independent variables. For ethnicity, we use a measure of race/ethnicity that combines both race and Hispanic ethnicity into a single variable, because this is the way the college collects race/ethnicity data.

In addition to course medium, independent course-level variables included a student's reason for taking the course (whether as an elective or to fulfill distributional or major requirements). The categorization of a course as an elective, distributional requirement, or major requirement was based on the requirements of the student's major as listed in the college catalog: electives were courses which did not fulfill any particular curriculum requirement (other than for general elective credits); distributional requirements were courses that fulfilled a degree requirement that was not a part of the major's core curriculum; and major requirements were courses that were either explicitly required as a part of the major's core curriculum, or which were elective courses in the major. Major requirements could be in the major field of study or in a related field.

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Data Analyses

To analyze factor structure of the survey, principal component factor analysis with varimax rotation was used, and to measure internal reliability, Cronbach's standardized alpha and Guttman's Fourth Lambda reliability coefficients were calculated. For analysis of the predictive validity of the online learning readiness survey scores and individual constructs, multilevel binary logistic regression models were used, with specific course taken as the lowest level, and student as the grouping factor. In this way courses were nested within students, and the model takes into account random effects by student, even for factors that are not explicitly included in the model. In other words, we expect some students to get higher grades in all of their courses on average than others, and while the factors included in the model may include some of these overall differences by student, it cannot possibly include them all. A multilevel model accounts for this correlation among outcomes in courses taken by the same student, and therefore better fits the structure of the data. Binary logistic regression models were also used to test whether or not the survey score correlated with subsequent online enrollment, by using course medium as the dependent variable.

RESULTS

Factor Structure of the E-learning Readiness Survey

A principal component factor analysis with varimax rotation on the twelve e-learning readiness survey questions (see the Appendix for the detailed survey) was used to assess factor structure and to obtain orthogonal inputs prior to implementing regression models. In this analysis, the first four factors had eigenvalues greater than one, so based on eigenvalues alone, we might want to limit our analysis to four underlying factors only. On the other hand, the first eight factors each individually explained over 5% of the total variance in survey score, and those

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eight factors together explained 82% of the total variance. A scree plot of the eigenvalues can be seen in Figure 1. Because both a four-factor structure and an eight-factor structure seem plausible, a principal component factor analysis with varimax rotation, on both four factors and again on eight factors, was run on the twelve e-learning readiness survey questions. The results for the eight-factor structure can be seen in *Table 2*.

In *Table 2*, one to two questions loads on each factor, and the demarcation between questions that do and do not load on a single factor is very clear in each case; the questions that load on each component do appear to share a conceptual meaning and the questions that load on different components do seem to measure different constructs, so this survey has good convergent and discriminant validity. We summarize the construct measured by each component factor in *Table 3*. These constructs are very similar to those constructs reported in the research literature (see *Table 1*).

In addition to exploring the factor structure of the survey, internal reliability of the full set of survey items and on the items that loaded on individual factors was also assessed. Guttman's Fourth Lambda reliability coefficient for the full survey was 0.81, which suggests a good level of reliability (George & Mallery, 2003; Nunnaly, 1978). Guttman's Fourth Lambda reliability coefficients for the first four factors, each of which contained two items, ranged from about 0.6-0.7, suggesting an acceptable level of reliability, particularly for two-item scales.

For the sake of brevity, information for the analysis on the four-factor analysis is not presented here, but the general factor structure in that analysis was: 1) academic skills (questions 5, 6, 9, 10, 11, 12); 2) computer access/skills/expertise (questions 2, 3, 4,); 3) oral versus written learning style (questions 7, 8); and 4) GPA (question 1). Guttman's fourth lambda for individual

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factors were similar to those obtained with the eight-factor scale, slightly higher on average and also in an acceptable range.

Predictive Validity of the E-learning Readiness Survey

To test the validity of the online readiness survey in predicting course outcomes, we used a multilevel logistic regression model with successful course completion as the dependent variable, where the random effects were modeled by student. Course delivery medium and various measures of scores on the e-learning readiness survey (in addition to the interaction between scores and course delivery medium) were modeled as fixed effects. The model was computed, first as a basic model with no other covariates, and then as a comprehensive model with ethnicity, gender, age, enrollment, G.P.A., income, financial aid status, and motivation for taking the course as fixed effects covariates; the interaction between course delivery medium and these covariates are also included in the model. The fixed effects odds ratios, along with standard errors and significance levels for these two models, where the individual scores for each student on each of the eight-factors of the survey (using the eight-factor model), can be seen in *Table 4*.

In considering the results of the two models of e-learning readiness survey factors and successful course completion, we can see that while factors C3, C4, and C5 (and C8 in the model without covariates) are significant predictors of successful course completion generally[3], they are no better at predicting differential online versus face-to-face course outcomes, because none of the interaction terms between the medium and any of the factors is significant in either model.

[3] We note that the coefficients in Table 4 show only that these factors were significant predictors of course outcomes in the face-to-face environment (because of the inclusion of the interactions between each factor and the course medium that were included in the model). However, models without the interaction terms (not included here for the sake of brevity), show similar patterns across all courses, regardless of course type. Throughout this paper, when we suggest that some measure of the online readiness survey was predictive of course outcomes generally, we intend this to imply that in addition to patterns observed for face-to-face courses visible in the models that include interactions, similar patterns were observed on average across course types in models without the interaction included.

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This suggests that while factors such as reading/writing skills, time management, and G.P.A. may predict how well a student will do in any course, they do not seem to predict how well a student will do in an online course specifically in comparison to a face-to-face course. The models shown in *Table 4* were also run using the four-factors obtained from the four-factor structure of the survey, and using each individual question as a predictor, and in both of those cases, the results were substantially similar to those reported in *Table 4*: none of the individual questions and none of the four-factors were significant predictors of differential online versus face-to-face performance.

In addition to running the model with individual constructs as independent variables, we ran another multilevel logistic model with the aggregate e-learning readiness survey score in place of the individual factors. This model was calculated, first with score, medium and their interaction, with no other covariates, then with all of the same covariates as in *Table 4* included in the model, where the interaction between course delivery medium and these covariates are also included in the model. The model was run a third time, this time removing the nonsignificant interaction between e-learning readiness survey score and course delivery medium, but retaining all other covariates and their interactions with course medium. The fixed effects odds ratios, along with standard errors and significance levels for these three models were all substantially similar to those reported in *Table 4* and so are not reported here, but the log likelihood and AIC values for each model can be seen in *Table 5*.

As before, the aggregate score on the e-learning readiness survey was a significant predictor of successful course completion in general (for both online and face-to-face courses) in all three models in *Table 5*, but in neither of the first two models was it a significant predictor of successful online course completion specifically (in comparison to face-to-face outcomes),

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which is why it was removed from the third model. In other words, the e-learning readiness survey score was no better at predicting online course outcomes than predicting face-to-face course outcomes. In particular, we note that the third model in *Table 5* is identical to the second model except for the exclusion of the nonsignificant interaction term between course medium and e-learning readiness survey score in the third model. Because the third model contains one fewer factor, we would expect its log likelihood value to go up, implying a worse fit. But in fact the models have the same log likelihood, and the AIC value for the model without the medium-by-score interaction term is actually lower, suggesting a better model fit without the interaction term, and therefore a better fit when survey score is not included as a predictor for differential online versus face-to-face outcomes.

Hybrid versus Fully Online Courses

The previous analysis was carried out with all online courses (both hybrid and fully online) combined into a single category. Research has suggested that outcomes in hybrid courses may be more similar to face-to-face than fully online courses. Therefore, we repeated the previous analysis after breaking down the online course category into two categories: hybrid and fully online.

For the new multilevel logistic model with online courses broken out into the two categories hybrid and fully online, successful course completion remains the dependent variable, and random effects are again modeled by student, with the aggregate e-learning readiness survey score as a fixed effect. The model was run, first with score, medium and their interaction, with no other covariates; then with all of the same covariates (and their interactions with medium) as before. The only variation was that, for the comprehensive model, the financial aid factor had to be removed because the subgroup size for hybrid courses in each subcategory was too small, and

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therefore the model encountered difficulties in minimizing the approximated deviance. As a result, the analysis included only one measure of SES. The fixed effects odds ratios, along with standard errors and significance levels for these three models can be seen in *Table 6*.

From the results in *Table 6*, we can see that while scores on the e-learning readiness survey do predict course outcomes generally, they still do not predict outcomes in e-learning courses any better than for face-to-face courses, even when e-learning courses are separated into the categories that differentiate between fully online and hybrid classes.

Relationship Between the e-learning Readiness Survey Score and a Student's Decision to Proceed with Online Course Enrollment

A large number of students took the e-learning readiness survey, indicating an intention to enroll in an online course, but never did so (only about one third of students who took the survey enrolled in an online course the following semester). Therefore, another crucial question to ask is whether requiring students to take the survey before enrolling in online courses may be related to their subsequent choice to enroll in online courses. The intent of the survey and the feedback provided to students is to discourage students with lower scores from enrolling in online courses. If the survey were a valid predictor of online course outcomes, then any evidence that scores on the survey are positively correlated with online course enrollment would suggest that the survey is fulfilling its purpose in this respect. However, if the survey is not a valid predictor of online course outcomes specifically (as the previous analysis in this article suggests), then any evidence that scores on the survey are positively correlated with online course enrollment shows instead that students who score lower on the survey may be needlessly discouraged from taking an online course, despite the fact that they are at no particular disadvantage in an online class. So we seek to determine if there is a positive correlation with the e-learning readiness survey score

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and online course enrollment. Hybrid and fully online courses were combined into a single category in this analysis, because the college in this study requires all students who are interested in enrolling in any online course, either hybrid or fully online, to take the survey, and survey results are presented uniformly to both groups. In this analysis a binary logistic regression model was run with e-learning survey score as the independent variable and enrollment in an online course in the year following the survey as the dependent variable. The model was run, first without any covariates, and then with all the covariates used in previous models. The results of these two models can be seen in *Table 7*.

From *Table 7* it is clear that the e-learning readiness survey score does have a highly significant positive correlation with online course enrollment in the year following the survey. This does not establish a causal relationship, since it is possible that students who scored highly on the survey just had different attributes that also made them more likely to enroll in an online course. However, we note that all students who took the survey did so because they were initially interested in registering for an online course, and invested at least some effort towards that end. This suggests that the survey could very well be discouraging some students from enrolling online, despite evidence that the survey is not an accurate predictor of a student's likelihood of doing significantly worse in an online course than a face-to-face course in comparison to their peers. Further research is clearly needed to determine to what extent this relationship between survey score and online course enrollment may be causal, and if it is causal, to determine the effects of a student's being discouraged from taking an online course on their college enrollment and persistence.

Student Characteristics and Predicting Online Course Outcomes

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Do Online Readiness Surveys do What They Claim?

We note that in the models used in this study, individual student characteristics were a significantly stronger predictor of differential online versus face-to-face course outcomes than the e-learning readiness score. Looking at the models in *Tables 5* and *6*, we can see that while Black students had significantly worse course outcomes face-to-face compared to White students, the gap between online and face-to-face outcomes was actually a bit smaller for these students, and that this difference in trend was significant ($p<0.05$). Similar results held for Hispanic students when comparing fully online course outcomes to face-to-face course incomes in *Table 6*. And while women did not have significantly better course outcomes than men face-to-face, their outcomes in the online environment were significantly better (particularly for fully online courses), and this interaction with course medium was significant.

Students who did not apply for financial aid had significantly better course outcomes face-to-face ($p<0.001$), and had a significantly larger gap between online and face-to-face outcomes than students who applied for financial aid but did not receive it ($p<0.001$). The reasons for this are unclear, but one possible explanation is that these students may have been less motivated or less self-directed on average, and it may have been these qualities which made them less likely to succeed in the online medium.

Limitations

This study was conducted at a single institution, and while that increases the internal reliability of the analysis, it means that caution should be exercised in overgeneralizing the applicability of the results. Because the institution which was the focus of this study is a large diverse urban community college, it seems likely that the results will apply to other large diverse urban community colleges. Further research is necessary in order to determine if similar conclusions can be drawn for four-year colleges and universities, for less diverse institutions, or

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for rural community colleges. Additionally, this study uses one measure of student success: course grade. However, there may be other measures of online student success that would be worth pursuing.

In addition, this study tested just one particular instrument for predictive validity for online course outcomes, so the results of this study cannot be generalized to other online readiness surveys. However, we would anticipate that online readiness surveys that test substantially similar constructs as the one in this study would likely return similar results. The instrument tested here does not test every possible theoretical construct that might work as a predictor of significantly larger-than-expected gaps between online and face-to-face course outcomes. Rather, this particular survey was selected because it is one that is actually used in practice at a large institution, and that seems to be fairly representative of the kinds of online readiness surveys used nationally. The survey closely resembles others currently implemented at other institutions, in terms of the constructs it tests, many of the specific questions it uses, and its shorter length. The survey's length also made it possible for it to be required for all students interested in online course-taking at the college in this study, which resulted in a particularly large sample size and allowed this study to avoid the coverage, sampling, and non-response error to an extent typically not possible in survey research. Further research is clearly needed to test a wider variety of online readiness surveys to determine to what extent surveys which test other constructs may be able to reliably predict outcomes in online courses specifically.

Furthermore, this survey uses statistical methods to calculate the probability of particular outcomes for individual students based on a set of specific characteristics. As with any research that uses these kinds of statistical models to analyze relationships between student characteristics and educational outcomes, this approach limits our view of individual students to a set of pre-

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defined characteristics instead of a holistic view of the whole person. Other qualitative studies, for example, which take a more holistic view of students who take online courses, might reveal other patterns and provide different information about how to best support these students.

This study also focuses on student characteristics; it does not focus on instruction, or institutional culture, or technological structures/resources, or advising/mentoring structures, for example. To best support online students, it is necessary to combine information from a wide variety of research that investigates different factors that impact student outcomes in these courses.

DISCUSSION AND IMPLICATIONS

Factor Structure of the e-learning Readiness Survey

Principal component factor analysis with varimax rotation suggested eight distinct underlying factors which explained 82% of the total variance in survey scores. These factors were: Oral versus written learning style; Computer experience/expertise; Reading/writing skills; Time management; G.P.A./academic preparation; Computer access; Confidence in online discussion as an effective learning method; and Help-seeking. The survey showed excellent convergent and discriminant validity, and the factors identified in the survey mirror most of the common constructs identified in the e-learning readiness survey literature. The factor analysis suggested an eight factor structure, and Cronbach’s standardized alpha and Guttman’s Fourth Lambda reliability coefficients both confirmed reliability of the instrument.

Predictive Validity of the e-learning Readiness Survey

While the survey score and some individual constructs (Reading/writing skills; Time management; G.P.A./academic preparation; Help-seeking) were significant predictors of overall course outcomes, none of these were predictive of online course outcomes specifically in

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comparison to face-to-face course outcomes. This means that the survey showed no predictive validity in identifying students who were likely to do significantly worse online than expected based on their face-to-face course performance, but rather that it was only effective in identifying students who are at risk of failing or dropping out in any medium.

Since it is possible that surveys that test other constructs (or that test the constructs used on this survey in a different way) may return different results, a logical next step would be to test online readiness survey instruments which focus more intensively on other constructs. For example, testing the predictive validity of a survey which focuses more intensively on self-directed learning and on motivation might produce better results. Only after testing a number of different types of instruments to determine whether they are valid predictors of differential online versus face-to-face course outcomes would it be possible to draw broader conclusions about whether these instruments are effective at identifying college students who are at-risk in online courses before they enroll.

Possible Effects of the Online Readiness Survey on Student Enrollment Decisions

The survey tested in this study demonstrated no ability to identify students who were at additional risk for failure when taking online classes. This lack of predictive validity suggests that making course choices based on online readiness surveys which are similar to the one used in this study is likely not an effective approach to improving online retention rates overall. Further, there was a clear and significant correlation between survey score and a student's likelihood of subsequently enrolling in an online course. This suggests that the online readiness survey in its current form may be arbitrarily discouraging some students from enrolling online. This is a concern because it suggests that in this case the administration of the survey may be reducing equal access for some students to college courses by discouraging them from taking

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courses online without a good justification for doing so[4]. In fact, it may result in some students enrolling in fewer college courses and therefore having a lower level of academic momentum, which is correlated with lower rates of college persistence (Attewell, Heil, & Reisel, 2011). Furthermore, links between online course-taking and college dropout are currently tentative, and there is some evidence that students who take courses online are actually more likely to obtain a college credential than their peers who take no online courses, once student characteristics are controlled (Shea & Bidjerano, 2014), so discouraging students from taking courses online could be both unnecessary and problematic in many cases.

The results of this study suggest that we should be particularly cautious in how we use online readiness assessments. Institutions currently using online readiness surveys may want to re-think the use of these instruments and instead consider alternative approaches to improving online retention (such as testing interventions aimed at supporting the course and college outcomes of online students), and assessments currently in use should be tested for validity in predicting differential online versus face-to-face course outcomes before they are implemented more widely.

Using Student Characteristics instead of Surveys to Identify At-Risk Students

In this study, the gaps between online and face-to-face course outcomes were smaller for female students compared with male students. The gaps were also smaller for Black and Hispanic compared to White students, even though Blacks and Hispanics had poorer course outcomes overall than White students (there was no overall difference in course outcomes by

[4] It is true that, in this college's implementation, students are not barred from taking online courses if they score poorly on the survey, but discouraging a student from taking a particular course may in some cases have the same net effect as prohibiting the student from registering. While a student may take a face-to-face course instead of an online course if they are discouraged by their survey results from enrolling online, it seems likely that some students may choose to take fewer courses or not to enroll at all if they are discouraged from taking a course online (e.g. if none of the available face-to-face courses fit well within their schedule or if they have personal or work obligations that make it difficult for them to attend regularly scheduled class meetings).

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gender). Because this study compared online and face-to-face course outcomes for the same student, these results are particularly striking. They suggest that future research which further explores online versus face-to-face course outcomes for Black, Hispanic and female students may be fruitful in helping us to better understand factors influencing online course performance as well as factors that may improve course outcomes for these groups that have been traditionally underrepresented in higher education. For example, it may be that because of the relative anonymity of the online environment, cues about ethnicity and gender are more subtle, and that therefore factors such as *stereotype threat* or *implicit bias* are triggered less often in the fully online environment, which could explain the smaller gap between successful course completion online versus face-to-face for these groups. Further research which explores this question more qualitatively may be able to shed light on this conjecture.

Various demographic characteristics and other institutionally collected data had a significant relationship with differential online versus face-to-face outcomes (while survey scores did not). This suggests that an alternate way to identify at-risk students is to build a model using data routinely collected by institutional research departments. This method would be less intrusive, less costly, and, as this study suggests, likely more reliable.

An additional question to confront is what to do with any results gleaned from the model. Even if models based on student characteristics can be shown to be reliable predictors of online course outcomes specifically, they may still not be suitable for use as a screening tool; for example, if ethnicity or gender are part of a model used to identify “at-risk” students, there are ethnical questions that transcend the model’s effectiveness, such as whether students should be advised not to take a particular course based on a model which uses ethnicity and gender as a part of its calculation of risk. Instead, we suggest that students identified by this early-warning

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model could be treated the way “at-risk” students in face-to-face classes are typically treated – with extra support such as advising, mentoring, tutoring, or technical help. Rather than administrative obstacles to or outright prevention from enrollment, this approach would better preserve the mission of open access to higher education while also improving the rates at which students successfully complete online courses.

CONCLUSIONS

The online readiness survey tested in this study was representative of the majority of such screening surveys currently used across the U.S. However, neither the whole survey score, nor individual questions, nor various factors extracted using principal component factor analysis were significant predictors of differential online versus face-to-face successful course completion. This demonstrates that this particular online readiness survey, and likely others that are similar to it, do not have any predictive validity in identifying students who are at higher risk in the online environment. In particular, student characteristics commonly obtained from institutional research departments were better predictors of differential online versus face-to-face performance.

Furthermore, there is evidence that the results of the online readiness survey discouraged students from enrolling in online courses even though these students were at no increased risk of poor outcomes online. This suggests that it is particularly vital that any surveys used as screening tools be tested rigorously for predictive validity before they are implemented. This could also mean that the use of the survey actually impeded degree progress for some students by encouraging them to enroll in fewer classes. Students who are interested in enrolling in online courses are significantly more likely to have characteristics that limit the quantity and flexibility of time that they have available for college—so if online courses are not available (or not

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perceived as a viable option as a result of the advice given by the online readiness survey), it is likely that some of these students will take fewer classes or will not enroll in college at all.

This suggests that surveys currently in use should be tested for predictive validity in identifying students at risk in the online environment specifically (as opposed to academic performance more generally). This can only be done by looking for the interaction between survey score or survey constructs and course medium to see if it is significant in predicting successful course completion—if the interaction is not significant in well-controlled studies, then the survey should be revised and retested until a significant interaction can be found, or should be discarded and replaced with alternative methods for identifying at-risk students.

Further, if colleges do identify a student as at-risk for increased failure in online courses, rather than screening these students out of online courses and consequently limiting their educational options, they should consider alternative approaches to boosting online retention. For example, one option would be to use models of risk based on student and course characteristics obtained from institutional research departments to identify groups of students and courses to be targeted for extra support online, such as additional tutoring, advising, mentoring or technical support.

In general, this research highlights two important points to consider when exploring ways to improve online outcomes: 1) Factors that predict overall academic outcomes are not necessarily good at identifying students who are at increased risk in the online environment (compared to their risk in traditional face-to-face classes); and 2) Any screening method that discourages students from taking online classes has the potential to negatively impact academic momentum and degree completion for students who do not substitute face-to-face for online classes, and therefore this should only be done when the screening method has been rigorously validated and

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there is significant evidence that this risk may outweigh the risk of online enrollment for those students. More research on factors that impact both the course outcomes and the college momentum of online students is clearly needed if institutions are to make evidence-based decisions about which policies are optimal for improving online course outcomes. In the meantime, institutions should be cautious about implementing untested online readiness surveys, and more broadly, they should carefully consider the potential impact of discouraging online enrollment on college progression and completion when implementing new approaches to reducing online course attrition.

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TABLES AND FIGURES

Table 1 Constructs identified in online readiness surveys

year	survey name	constructs measured
1993	MLSQ	motivation (subscales: intrinsic goal orientation, extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning and performances, and test anxiety); cognitive learning strategies (subscales: rehearsal, elaboration, organization, critical thinking, meta-cognitive self-regulation, time and study environment management, effort regulation, peer learning, and help seeking)
1999	BISL	personal, social and environmental aspects of self-directed learning
2000	OTSES	internet self-efficacy
2000/ 2001	McVay/ROC	comfort with eLearning; self-management of learning
2001	SmarterMeasure/ READI	reading speed and recall; typing speed and accuracy; learning styles; technical competency; and individual attributes such as motivation, procrastination, willingness to seek help, and persistence
2001	SDLR	self-management; desire for learning; self-control
2003	MEBIR	familiarity with and mastery of the Internet; perception that Internet coursework is more flexible and convenient; perception that internet courses will be of higher quality
2003	Maki	1) personal characteristics (extraversion, agreeableness, conscientiousness, emotional stability, intellectualism); 2) expected liking of the course; enjoyment of class discussion; computer experience/anxiety; organizational skills; independence; confidence about course expectations
2004	McVay revised	confidence in prerequisite skills; self-direction and initiative; desire for interaction; beliefs about distance education
2004	DeTure	online technology self-efficacy; field dependence/independence
2004	Watkins	comfort with online skills and relationships; comfort with online audio/video; comfort with internet discussions; beliefs about what is necessary for course success; motivation
2005	Waschull	personal traits; self-discipline/motivation; access to technology; lifestyle factors
2006	TOOLS	computer skills; independent learning; dependent learning; need for online learning; academic skills
2007	TSROL	technical skills; computer self-efficacy; learner preferences; attitudes towards computers
2009	Cross	technical knowledge; reading level; independence; self-discipline
2010	OLRS	computer/internet self-efficacy; online communication self-efficacy; self-directed learning; learner control; motivation for learning
2011	Dray	purposes for internet use; ability to use email attachments; frequency of internet use; comfort with expressing opinions in writing; access to technology at home

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Table 2 Principal component factor analysis on e-learning readiness survey questions with eight underlying factors selected, using varimax rotation

	C1	C2	C3	C4	C5	C6	C7	C8
q1	0.05	0.00	0.01	0.04	0.99	0.01	0.01	0.03
q2	0.07	0.14	0.06	0.07	0.02	0.98	0.04	0.03
q3	0.09	0.76	0.28	0.12	-0.05	0.16	0.07	0.08
q4	0.08	0.88	0.09	0.13	0.04	0.03	0.06	0.06
q5	0.11	0.21	0.77	0.11	0.03	0.01	0.06	0.18
q6	0.11	0.12	0.16	0.15	0.03	0.03	0.06	0.95
q7	0.85	0.12	0.09	0.04	0.06	0.02	-0.01	0.06
q8	0.85	0.04	0.12	0.11	-0.01	0.06	0.04	0.06
q9	0.12	0.12	0.80	0.23	-0.02	0.07	0.06	0.01
q10	0.02	0.10	0.10	0.15	0.01	0.04	0.97	0.05
q11	0.04	0.08	0.23	0.75	0.09	0.03	0.16	0.12
q12	0.12	0.16	0.11	0.84	-0.03	0.05	0.03	0.05
Eigenvalues	1.52	1.50	1.45	1.44	1.01	1.00	0.99	0.98
Proportion Variance	0.13	0.12	0.12	0.12	0.08	0.08	0.08	0.08
Cumulative Variance	0.13	0.25	0.37	0.49	0.58	0.66	0.74	0.82
Proportion Explained	0.15	0.15	0.15	0.15	0.10	0.10	0.10	0.10
Cumulative Proportion	0.15	0.31	0.45	0.60	0.70	0.80	0.90	1.00

Individual survey questions can be found in the *Appendix*.

Table 3 Interpretation of constructs measured by each component of the rotated principal component factor analysis on e-learning readiness survey questions

component	survey questions	construct measured
C1	q7, q8	Oral versus written learning style
C2	q3, q4	Computer experience/expertise
C3	q5, q9	Reading/writing skills
C4	q11, q12	Time management
C5	q1	G.P.A./academic preparation
C6	q2	Computer access
C7	q10	Confidence in online discussion as an effective learning method
C8	q6	Help-seeking

For detailed survey questions, see the *Appendix*.

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Table 4 Multilevel Model (random effects modeled by student), Logistic Regression Models for Successful[1] Course Outcomes by e-learning Readiness Survey Factors, with and without Covariates (Fixed Effects Odds Ratios Reported)

		basic model			comprehensive model		
	(Intercept)	3.71	(0.11)	***	3.62	(0.62)	***
medium	online	0.43	(0.03)	***	0.14	(0.11)	*
factor	C1	1.04	(0.03)		1.01	(0.03)	
	C2	1.05	(0.03)		0.99	(0.03)	
	C3	0.93	(0.03)	*	0.94	(0.03)	*
	C4	1.06	(0.03)	*	1.06	(0.03)	*
	C5	1.91	(0.06)	***	1.57	(0.06)	***
	C6	0.99	(0.03)		0.98	(0.03)	
	C7	0.97	(0.03)		0.98	(0.03)	
	C8	1.08	(0.03)	*	1.02	(0.03)	
ethnicity (*Ref. gp: White*)	American Indian or Native Alaskan				2.22	(1.69)	
	Asian or Pacific Islander				1.09	(0.12)	
	Black				0.69	(0.06)	***
	Hispanic				0.75	(0.07)	**
gender	F				1.06	(0.07)	
age	24 or over				1.32	(0.08)	***
enrollment	PT				0.93	(0.05)	
G.P.A.	1.67-2.66				0.86	(0.08)	
(*Ref. gp: 0-1.66*)	2.67-3.66				1.43	(0.14)	***
	3.67-4.00				2.52	(0.34)	***
	none				2.46	(0.26)	***
income	income				1.00	(0.00)	
financial aid (*Ref. gp: none*)	AFDC				0.63	(0.05)	***
	Pell				0.75	(0.05)	***
	did not apply				2.86	(0.32)	***
motivation (*Ref. gp: elective*)	dis req.				0.75	(0.05)	***
	major req.				1.24	(0.10)	**
	nonmatriculated				2.43	(1.05)	*
medium:factor	online:C1	1.02			1.03	(0.08)	
	online:C2	0.95			0.96	(0.07)	
	online:C3	1.07			1.02	(0.08)	
	online:C4	1.05			1.03	(0.07)	
	online:C5	1.09			0.96	(0.08)	
	online:C6	1.09			1.12	(0.08)	
	online:C7	0.93			0.94	(0.06)	
	online:C8	0.92			0.92	(0.06)	

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medium: ethnicity	online:American Indian or Native Alaskan		0.97	(1.23)	
	online:Asian or Pacific Islander		1.24	(0.32)	
	online:Black		1.58	(0.32)	*
	online:Hispanic		1.23	(0.26)	
medium: gender	online:F		1.27	(0.20)	
medium:age	online:24 or over		1.11	(0.15)	
medium: enrollment	online:PT		1.15	(0.18)	
medium:G.P.A.	online:1.67-2.66		1.42	(0.98)	
	online:2.67-3.66		2.40	(1.66)	
	online:3.67-4.00		2.98	(2.15)	
	online:none		1.67	(1.22)	
medium: income	online:income		1.00	(0.00)	
medium: financial aid	online:AFDC		0.77	(0.16)	
	online:Pell		0.72	(0.13)	·
	online:did not apply		0.37	(0.09)	***
medium: motivation	online:dis req.		1.20	(0.26)	
	online:major req.		1.11	(0.29)	
	online: nonmatriculated		0.93	(0.66)	
	n	24,006	24,006		
	-2 Log Likelihood	-12,746	-12,441		
	AIC	25,529	24,965		

[1]Successful course outcome denotes completion of the course with a C- average or better.
· p<0.10, * p<0.05, ** p<0.01, *** p<0.001

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Table 5 Multilevel Model (random effects modeled by student), Logistic Regression Models for Successful[1] Course Outcomes by e-learning Readiness Survey Score, Course Delivery Medium, and Student Characteristics (Fixed Effects Odds Ratios Reported)

	score only model	**comprehensive model**	**comprehensive model without score interaction**
n	24,006	24,006	24,006
-2 Log Likelihood	-12,945	-12,441	-12,441
AIC	25,900	24,965	24,963

[1]Successful course outcome denotes completion of the course with a C- average or better.
· p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 6 Multilevel Model (random effects modeled by student), Logistic Regression Models for Successful[1] Course Outcomes by e-learning Readiness Survey Score, Course Delivery Medium (with hybrid courses broken out), and Student Characteristics (Fixed Effects Odds Ratios Reported)

		score-only model			**comprehensive model**		
	(Intercept)	0.35	(0.12)	**	1.00	(0.35)	
score	score	1.06	(0.01)	***	1.02	(0.01)	*
medium	hybrid	0.24	(0.35)		0.48	(0.96)	
	online	0.17	(0.15)	*	0.00	(0.00)	
ethnicity (*Ref. gp: White*)	American Indian or Native Alaskan				1.71	(1.30)	
	Asian or Pacific Islander				1.17	(0.13)	
	Black				0.58	(0.05)	***
	Hispanic				0.62	(0.06)	***
gender	F				1.02	(0.06)	
age	24 or over				1.39	(0.08)	***
enrollment	PT				1.26	(0.06)	***
G.P.A. (*Ref. gp: 0-1.66*)	1.67-2.66				1.03	(0.09)	
	2.67-3.66				2.08	(0.20)	***
	3.67-4.00				4.67	(0.60)	***
	none				2.34	(0.25)	***
income	income				1.00	(0.00)	*
motivation (*Ref. gp: elective*)	dist. req.				0.75	(0.05)	***
	major req.				1.21	(0.10)	*
	nonmatriculated				2.68	(1.15)	*
medium: score	hybrid:score	1.02	(0.04)		1.02	(0.04)	
medium: ethnicity	online:score	1.02	(0.02)		1.01	(0.02)	
	hybrid:American Indian or Native Alaskan				0.00	(0.00)	

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	online:American Indian or Native Alaskan		84,556	(20,305,332)	
	hybrid:Asian or Pacific Islander		0.87	(0.46)	
	online:Asian or Pacific Islander		1.40	(0.40)	
	hybrid:Black		1.25	(0.52)	
	online:Black		1.76	(0.39)	*
	hybrid:Hispanic		0.51	(0.21)	
	online:Hispanic		1.63	(0.37)	*
medium: gender	hybrid:F		1.12	(0.34)	
	online:F		1.41	(0.24)	*
medium:age	hybrid:24 or over		0.93	(0.27)	
	online:24 or over		1.04	(0.16)	
medium: enrollment	hybrid:PT		1.48	(0.48)	
	online:PT		1.21	(0.18)	
medium: G.P.A.	hybrid:1.67-2.66		0.41	(0.36)	
	online:1.67-2.66		303,367	(36,024,842)	
	hybrid:2.67-3.66		0.61	(0.53)	
	online:2.67-3.66		553,550	(65,734,198)	
	hybrid:3.67-4.00		0.47	(0.45)	
	online:3.67-4.00		690,230	(81,965,106)	
	hybrid:none		0.38	(0.36)	
	online:none		434,512	(51,598,497)	
medium: income	hybrid:income		1.00	(0.01)	
	online:income		1.00	(0.00)	
medium: motivation	hybrid:dist. req.		1.05	(0.66)	
	online:dist. req.		1.10	(0.25)	
	hybrid:major req.		1.33	(0.95)	
	online:major req.		0.93	(0.25)	
	hybrid: nonmatriculated		0.06	(0.09)	·
	online: nonmatriculated		2.67	(2.47)	
	n	24,006	24,006		
	-2 Log Likelihood	-12,943	-12,527		
	AIC	25,901	25,158		

[1]Successful course outcome denotes completion of the course with a C- average or better.
· p<0.10, * p<0.05, ** p<0.01, *** p<0.001

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Table 7 Logistic Regression Models for Online Course Enrollment by e-learning Readiness Survey Score

		score-only model			comprehensive model		
	(Intercept)	0.01	(0.00)	***	0.01	(0.00)	***
score	score	1.12	(0.00)	***	1.11	(0.00)	***
ethnicity (*Ref. gp: White*)	American Indian or Native Alaskan				1.60	(0.53)	
	Asian or Pacific Islander				1.07	(0.05)	
	Black				1.06	(0.05)	
	Hispanic				0.99	(0.04)	
gender	F				1.44	(0.05)	***
age	24 or over				1.24	(0.04)	***
enrollment	PT				0.76	(0.03)	***
G.P.A. (*Ref. gp: 1.67-2.66*)	0-1.66				0.23	(0.02)	***
	2.67-3.66				1.24	(0.04)	***
	3.67-4.00				1.24	(0.06)	***
	none				0.57	(0.03)	***
income	income				1.00	(0.00)	·
financial aid (*Ref. gp: none*)	AFDC				1.04	(0.05)	
	Pell				1.02	(0.04)	
	did not apply				1.57	(0.09)	***
motivation (*Ref. gp: elective*)	dist. req.				1.06	(0.05)	
	major req.				1.24	(0.07)	***
	nonmatriculated				0.87	(0.14)	
n		24,006			24,006		
-2 Log Likelihood		-15,363			-14,832		
AIC		30,731			29,704		

· p<0.10, * p<0.05, ** p<0.01, *** p<0.001

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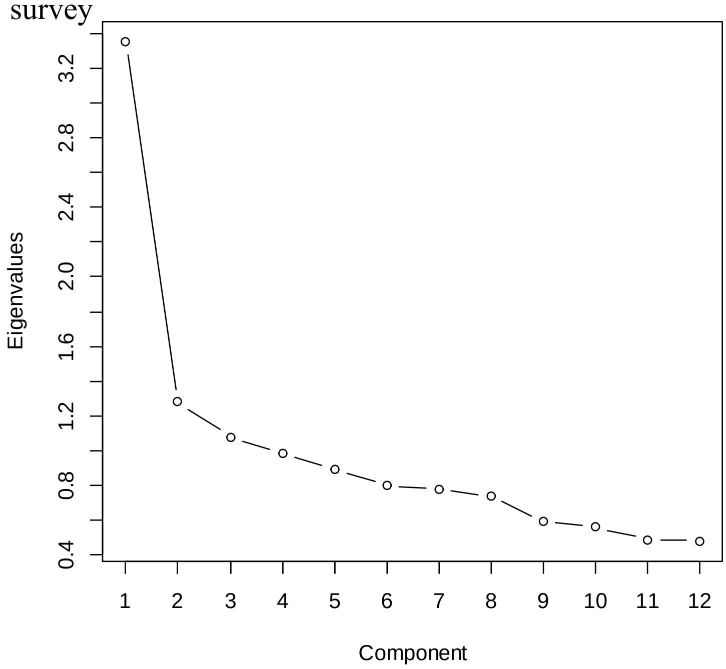
Figure 1 Scree plot of eigenvalues for 12-factor principal component factor analysis on 12 question e-learning readiness survey



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APPENDIX

E-learning Readiness Survey Questions

1. My GPA is: No G.P.A. (new transfer or new freshman); Between 2.0-3.0; Between 3.0-3.5; Above 3.5
2. I have access to a computer: At home or anywhere with my laptop; At home; At work and on college computers; Through a friend and on college computers
3. My experience using a web browser and navigating the Internet is: Excellent, I am very comfortable finding information online and can often help others; Good, I am usually comfortable finding information online; Average, I am not always comfortable, but try anyway; Slower than average, I am not comfortable and don't desire to try
4. I have experience creating documents using Microsoft Word and feel comfortable attaching files to e-mail messages: I am an expert; My skills are good or average; My skills are below average; I do not know how to use Microsoft Word
5. As a reader, I would consider myself: Good, I have no trouble reading and understanding text; Average, I usually understand text without help; Below average, I often need help to understand text; Poor, I am not a good reader
6. If a new subject is introduced or if I am given an assignment: I usually don't need much help understanding it; I am comfortable e-mailing an instructor to ask for clarification; I am uncomfortable e-mailing an instructor, but do it anyway; I never approach an instructor to admit I don't understand something
7. Regular face-to-to face contact with my professor is: Essential to my understanding a concept; Would be helpful to my understanding a concept; Not essential to my learning, as long as I am in contact with him/her; Not essential to my learning

8. I learn better when I listen to my professor explain a concept rather than reading from the course materials: Always true; Frequently true if the subject is difficult for me; Occasionally true, but I can usually learn by reading text; Rarely true even if the subject is difficult
9. Expressing my thoughts in writing is: Easy for me; Usually easy, but I need practice; Sometimes difficult; Almost always difficult
10. I believe participating in discussions through an online forum or through e-mail: Would help me learn; Could potentially help me learn, but I'm not certain; I've never tried it, so I'm not certain; Would not help me learn
11. I would classify myself as someone who is generally: Self-motivated and always gets things done ahead of time; Self-motivated and sometimes gets things done ahead of time; Needs reminding to get things done on time; Puts things off until the last minute or doesn't complete them.
12. Planning the order of class tasks and following a schedule is: Easy for me; Sometimes difficult, but I will make time for my online class; Often difficult, due to my work and family obligations; Usually difficult for me