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Testing a model to predict online cheating—Much ado about nothing

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Abstract

Much has been written about student and faculty opinions on academic integrity in testing. Currently, concerns appear to focus more narrowly on online testing, generally based on anecdotal assumptions that online students are more likely to engage in academic dishonesty in testing than students in traditional on-campus courses. To address such assumptions, a statistical model to predict examination scores was recently used to predict academic dishonesty in testing. Using measures of human capital variables (for example, grade point average, class rank) to predict examination scores, the model provides for a comparison of R^2 statistics. This model proposes that the more human capital variables explain variation in examination scores, the more likely the examination scores reflect students' abilities and the less likely academic dishonesty was involved in testing. The only study to employ this model did provide some support for the assertion that lack of test monitoring in online courses may result in a greater degree of academic dishonesty. In this study, however, a further test of the predictive model resulted in contradictory findings. The disparate findings between prior research and the current study may have been due to the use of additional control variables and techniques designed to limit academic dishonesty in online testing.

Keywords

Online cheating, predicting academic dishonesty

Academic dishonesty and faculty perceptions of online cheating

Student academic dishonesty includes a wide range of unacceptable behaviors and has been empirically studied for decades. Recently, a meta-analysis of studies on student academic dishonesty found that the prevalence of total (examinations, homework and plagiarism) academic dishonesty ranged from 9% to 95% with a mean of 70.4% (Whitley, 1998). Although academic dishonesty has long been an educational concern, some seem to view academic dishonesty as a new millennial behavior caused by the advent of online courses. This current focus on academic dishonesty in online courses may be the result of perceptions that online learning lends itself easily to cheating (Fontaine, 2012; McNabb and Olmstead, 2009) due to the "lack of face-to-face contact between

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the students and instructor" (McNabb and Olmstead, 2009: 210). It may also be the result of perceptions that tech-savvy students manipulate technology to "ace online courses with minimal effort" (Fontaine, 2012: A1). Nonetheless, such contentions about online cheating have not been strongly supported by the scant number of empirical studies on this topic, most of which have focused primarily on measuring perceptions of online cheating.

In general, findings from faculty surveys indicate a belief that online environments facilitate cheating (Kennedy et al., 2000). However, such opinions may be influenced by familiarity and experience with online teaching and learning. For example, Kennedy et al. (2000) found that having taught an online course reduced the percentage of faculty that believed it is easier to cheat in online courses (Kennedy et al., 2000). Yates and Beaudrie (2009) also found that those most concerned with academic dishonesty in online courses appear to be faculty with no experience in online teaching and learning. Results from their survey indicated that "instructors who do not teach distance education courses found the idea of online testing completely objectionable and believed the approach should not be used" (Yates and Beaudrie, 2009: 65). Faculty who taught online courses with monitored testing (that is, hybrid courses) were skeptical about online testing, and faculty who taught fully online (including testing) courses believed that there is no discernible test grade differences between online courses and traditional on-campus courses (Yates and Beaudrie, 2009). A survey of faculty teaching online within the University of Texas system also found that the majority of online faculty surveyed did not believe that there is a difference in cheating between online and face-to-face (F2F) students (McNabb and Olmstead, 2009).

Student perceptions and self-reports of online cheating

The results from student surveys show a similar trend as was found in faculty surveys—those less familiar with online learning were more likely to "perceive" cheating to be easier in online courses. For example, Kennedy et al. (2000) surveyed behaviors and perceptions of 172 online and F2F students and found that 57% believed that cheating would be easier in online classes, but having taken an online course reduces that perception. Charlesworth et al. (2006) surveyed perceptions of students required to use a web-based component in a hybrid class and found that 40% of students surveyed thought online assessments would encourage more cheating, while another 42% thought there would be no difference. Finally, Harmon et al. (2010) found that 59% of students perceived the frequency of cheating to be about the same in online and F2F formats.

Surveys of self-reported behavior of online and F2F students indicate that there is no difference in overall academic dishonesty between online and F2F courses, except, perhaps, during online testing. For example, a survey of 1305 students at two universities found that online students were more likely to use unpermitted notes (cheat sheets) during testing than students taking monitored tests. Nonetheless, students did report using cheat sheets under both conditions—monitored and unmonitored testing (Stephens et al., 2007). Similarly, surveys of 635 students in both F2F and online courses did find that online students were significantly more likely to obtain answers from others during an online test, but that "cheating in online courses is no more rampant than cheating in live classes" (Watson and Sottile, 2010). Indeed, a self-report survey study of 796 undergraduate online students indicated that the level of cheating in an online course was consistent with that of a F2F class during a single semester (Grijalva et al., 2006). Only one study of self-reported behavior found online students were less likely to cheat than F2F students (Stuber-McEwen et al., 2009).

Thus, survey research focusing on academic dishonesty in online testing has provided mixed and inconclusive results. Empirical studies incorporating predictive models and more direct comparative analyses have not, however, shed light on this topic, albeit there have only been two such studies.

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Predicting academic dishonesty in testing

Harmon and Lambrinos (2008) used a statistical model, originally created to predict examination scores, to predict academic dishonesty in testing. In this model, examination scores are predicted from human capital variables, which included grade point average (GPA), level of maturity (defined by age and class ranking) and whether the student was a major in the course being examined. Harmon and Lambrinos (2008) posited that if cheating was not occurring, then the model would have the same explanatory power for both monitored and unmonitored tests, with the unmonitored tests being taken online. The results of the Harmon and Lambrinos' (2008) study indicated that GPA was the only substantive explanatory human capital variable, with the other variables being statistically insignificant. Furthermore, the R^2 (0.4972) for the monitored final examination was substantially higher than the R^2 (0.0008) for the unmonitored final examination. Because GPA explained a greater amount of variation in examination scores for the monitored final, Harmon and Lambrinos (2008) suggest that more cheating occurred with the online, unmonitored final examinations.

Yates and Beaudrie (2009) compared the impact of monitored testing on final course grades, using a large sample of online education mathematics courses. The authors compared 406 grades of students who were evaluated in a monitored testing environment with 444 grades of students who were evaluated fully online with unmonitored testing and found no significant difference in grades between the two groups (Yates and Beaudrie, 2009). In a critique of the Yates and Beaudrie's (2009) study, Englander et al. (2011) note several important factors that may have influenced the results in Yates and Beaudrie (2009): (1) selection bias, (2) inappropriate outcome measure, (3) lack of uniformity in techniques to suppress cheating, (4) changes in online resources over time, and (5) overstatement of conclusions.

Englander et al.'s (2011) discussion of selection bias in the Yates and Beaudrie's (2009) study also highlights a failure to include cumulative GPA or other measures of student ability, since prior research notes an inverse relationship between cheating and academic ability and cheaters may have been more likely to register for the online courses (Englander et al., 2011). However, Yates and Beaudrie (2009) point out students did not know the format of the examinations; still, students may have assumed that an online course provided online tests. Englander et al. (2011) suggest test grades (instead of course grades) may have been a more appropriate outcome measure in the Yates and Beaudrie's (2009) study, since the study focused on whether tests that are not monitored contribute to cheating. Englander et al. (2011) also note that Yates and Beaudrie (2009) did not provide a clear description of precautions taken to prevent cheating; thus, it is not known if there was uniformity in techniques to suppress cheating. Finally, Englander et al. (2011) argue that history effects may have influenced study outcomes in Yates and Beaudrie (2009), since the study took place over a 6-year period during which time refinements in technology may have influenced test scores, and they suggest that Yates and Beaudrie (2009) overstate study conclusions. Englander et al. (2011) are quick to praise Yates and Beaudrie (2009) and note that their critique of the study "should not obscure the serious and important contribution they have made to this critical topic in contemporary education." Nonetheless, the Englander et al.'s (2011) critique provides important direction for research, particularly since there has been so little done in this area.

Although the integrity of online testing is a salient educational issue, few studies have explored it. Faculty and student surveys regarding academic dishonesty in traditional and online courses have provided a wealth of information over the decades. Nonetheless, surveys of perceptions may only provide a summary of anecdotal information, influenced by the individual's experience (or lack of experience) with online courses. Student self-report surveys of cheating may also present biased information. Another approach to address the question of integrity in online testing has been

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to compare assessment outcomes across course delivery modes. To be sure, a vast amount of research has amassed over the years comparing assessment outcomes between online courses and F2F courses (e.g. see Russell, 2001). Nonetheless, the focus of those studies has been to demonstrate that distance teaching and learning is equal to traditional teaching and learning. Recently, Harmon and Lambrinos (2008) and Yates and Beaudrie (2009) have explored the issue of academic dishonesty in online testing utilizing comparisons of test scores and more sophisticated statistical predictive models. However, those two studies present disparate findings and highlight the need for additional studies, incorporating additional variables and outcome measures, and have presented the additional concern of whether students who are likely to cheat on test are also more likely to enroll in online courses.

Research on the relationship between online courses and academic dishonesty has influenced the development of the following research questions to explore: (1) Is there a significant difference in examination scores between monitored and unmonitored online tests, when incorporating techniques to suppress cheating in both environments, controlling for history effects, and holding constant type of course and teaching techniques? This question provides an assessment of the impact of monitoring on examination scores addressing the research critique of Englander et al. (2011) by using examination scores instead of course grades and controlling for history effects. (2) Are students with lower GPAs more likely to enroll in online courses? This question addresses the issue raised by Englander et al. (2011) that research notes an inverse relationship between students with low GPAs and cheating, and the suggestion made by Englander et al. (2011) that students with low GPAs may be more likely to enroll in online courses because of a perception that it is easier to cheat with online tests. (3) Do student characteristics explain a greater degree of variation in examination scores for monitored tests, when incorporating techniques to suppress cheating in both environments, controlling for history effects, and holding constant type of course and instructor? This question incorporates information from the Harmon and Lambrinos' (2008) study, which suggests that if online students are more likely to cheat on tests, then the R^2 statistic will be lower for unmonitored tests compared to monitored tests. In other words, GPA will explain a greater amount of variation in the examination results for monitored tests. However, Harmon and Lambrinos (2008) did not discuss whether techniques to suppress cheating were utilized in the online environment, they did not control for history effects (one examination was taken in 2004 and the other in 2005), and they did not discuss whether the instructor was the same for both courses in their study and pedagogy may certainly influence test scores.

Methods

The data in this study consisted of student scores on mid-term and final tests from three sections of an introductory course. Information from university records on academic major (scored as either 0 for non-major or 1 for major), GPA, and cumulative credit hours was collected for each student enrolled in the three sections of the course. The statistical model that has been used to predict academic dishonesty in testing is

$$\mathrm{EXAM}(i) = \mathrm{b}_0 + \mathrm{b}_1\mathrm{GPA} + \mathrm{b}_2\mathrm{SOPHOMORE} + \mathrm{b}_3\mathrm{JUNIOR} + \mathrm{b}_4\mathrm{SENIOR} + \mathrm{b}_5\mathrm{MAJOR} + \mathrm{b}_6\mathrm{AGE} + \mathrm{U}_\mathrm{J}$$

The variable exam represents students' scores on both the mid-term examination and the final examination. A student's GPA provides a measurement of student ability, and student's age and academic ranking (first-year freshman, second-year sophomore, third-year junior, and fourth/

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fifth-year senior) define the student's experience in academics and level of maturity. The student's major is included in the equation, because students majoring in a discipline are "expected to have greater motivation to perform well" (Harmon and Lambrinos, 2008: 121). For the purposes of the current study, and based on findings in research, the above predictive model was somewhat modified

$$\text{EXAM}(i) = b_0 + b_1\text{GPA} + b_2\text{CUMULATIVE CREDIT HOURS} + b_3\text{MAJOR} + U_J$$

Because data were collected after the completion of the three sections of the course, it was not possible to ask students their ages. Thus, age was not included as a measure of maturity. However, the majority of undergraduate students on the campus where the sample was obtained are traditional students. Students over 25 years comprise only about 14% of the entire (13,513) student population (University of Wisconsin Oshkosh, 2011), and, no doubt, the majority of that 14% are enrolled in graduate programs. Consequently, there would have been little if any variation in age. Furthermore, Harmon and Lambrinos (2008) found that age did not increase the explanatory power of R^2 in their model; therefore, the exclusion of the age variable should not have altered the explanatory power of the predictive model in this study. Additionally, this study used earned credit hours, at the beginning of the semester, as a measure of academic experience, instead of class ranking. Harmon and Lambrinos (2008) did not find class ranking to be a significant predictor in their model. Since class ranking is an ordinal-level variable, it was anticipated that using a ratio-level measure (credit hours) of academic experience would increase the explanatory power of the predictive model.

The sample in this study included students from three sections of the same courses, taught during the spring 2012 semester, by the same instructor. There was one online section with unmonitored examinations ($N = 19$), one online hybrid section with monitored examinations ($N = 21$), and one F2F section with monitored examinations ($N = 60$). Prior to enrollment, students did not know whether examinations would be monitored or unmonitored; thus, selection bias was unlikely. It is possible, however, that some students may have assumed that the online and hybrid sections of the course included online testing. The course content, requirements, tests, and instructor were the same for the three sections. The only difference between the sections of the course was whether examinations were monitored on campus and whether students sat for the examinations on a Thursday or Friday of the same week. Although all three sections of the course had weekly quizzes and assignments, this study focused only on examination grades, as has been suggested by research.

Each section of the course had mid-term and final examinations. All examinations contained 50 questions with multiple response sets, had the same questions and response sets across sections, had a time limit of 70 minutes, and were taken on either a Thursday or Friday of the same week. In the F2F section, testing was monitored by the instructor. Prior to taking the examinations, students were warned not to engage in academic dishonesty and advised of the consequences of academic dishonesty in testing. In the F2F section of the course, examinations were scheduled on a Thursday. In the online section with monitored testing, the monitoring was conducted by the campus testing services department, which was told that students were not permitted to have any materials (notes, phones, etc.) except a pencil, the examination, and a scantron (a computerized sheet to mark answers). Students taking examinations in testing services were permitted to schedule the examinations on either the same Thursday as the F2F course, or the next day (Friday). Students had to provide identification and signature before taking an examination in testing services, and were also warned against using academic dishonesty and advised of the consequences of academic dishonesty. All hard copies of the examinations and scantrons were returned to the instructor, immediately after testing.

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Table 1. Average examination scores.

Variable	Monitored examinations			Unmonitored examinations			t-test
	Mean	SD	Number of observations	Mean	SD	Number of observations	
Mid-term	37.75	5.19	80	38.47	5.78	19	0.534
Final	40.21	4.72	80	40.63	4.79	19	0.347
GPA	2.68	0.475	80	2.80	0.520	19	0.937
Credit hours	58.31	28.55	80	50.31	25.18	19	−1.121
Major = 1	0.36	0.509	80	0.32	0.582	19	−0.350

SD: standard deviation; GPA: grade point average.

In the online section *without* monitored testing, the examinations contained the same questions and response sets as the other sections of the course. However, the questions were randomized for each online student so each received a unique test. For example, what might appear as question 37 on one mid-term examination would appear as question 45 on another mid-term examination. Additionally, students could not exit and restart an online examination once they began testing, only one question at a time was presented (to prevent copying the examinations), students could not move backward through the questions (to discourage the use of cheat sheets by limiting time), and the examination automatically submitted after the specified amount of testing time expired (also to discourage the use of cheat sheets). Once the examination was submitted, students could not view the examination again. The online examinations were also available for 2 days—Thursday and Friday of the same week, on the same dates as the examinations in the other sections of the course. Obviously, students could take an online examination anywhere they had access to the internet. Finally, online students were warned not to engage in academic dishonesty. As an additional deterrent to academic dishonesty, a message is posted on the online course site advising students that much of what they do online can be viewed by the instructor.

Results

Comparisons of means and R^2 statistics, t-tests, analysis of variance (ANOVA), and regression analyses were conducted Table 1 depicts the statistical mean for all variables in the study, except the variable "major" as it is a nominal-level variable.

To address the question of whether there is a difference in examination scores between on-campus monitored testing and online unmonitored testing, t-tests were conducted. As indicated in Table 1, there were no significant differences in examination scores between groups of monitored and unmonitored testing for the mid-term examination (t = 0.534, p > 0.05) or the final examination (t = 0.347, p > 0.05). In fact, the differences in the averages between the monitored and unmonitored testing groups, for both the mid-term examination (monitored, M = 37.75, standard deviation (SD) = 5.19; unmonitored, M = 38.47, SD = 5.78) and final examination (monitored M = 40.21, SD = 4.72; unmonitored M = 40.63, SD = 4.79), are so small that they can be measured in tenths of a point. To explore this question further, ANOVA was conducted for each examination between course delivery modes (online, hybrid, and F2F), and the results also indicated no significant difference in scores (mid-term, F = 0.239, p = 0.788; final, F = 0.141, p = 0.869).

A difference of means test was also used to address the question of whether students with low GPAs are more likely to enroll in online courses. As indicated in Table 1, there was no significant

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Table 2. GPA as a determinant of examination scores by testing type.

Variable	Mid-term examination		Final examination	
	Monitored	Unmonitored	Monitored	Unmonitored
Intercept (standard error)	23.761 (3.446)	24.108 (4.490)	27.548 (3.401)	25.827 (3.460)
GPA (standard error)	6.032 (1.295)	5.003 (1.555)	4.776 (1.278)	5.199 (1.198)
R^2	0.276	0.214	0.197	0.331
F	21.699*	10.353*	13.969*	18.826*
N	80	19	80	19

GPA: grade point average.
*Significant at 0.01.

Table 3. GPA as a determinant of test scores by course delivery mode.

Variable	Mid-term examination			Final examination		
	Online unmonitored	Hybrid monitored	F2F monitored	Online unmonitored	Hybrid monitored	F2F monitored
Intercept (standard error)	21.965 (6.542)	25.802 (6.453)	21.761 (3.446)	24.220 (4.945)	27.119 (5.057)	27.548 (3.401)
GPA (standard error)	5.876 (2.292)	4.316 (2.212)	6.032 (1.295)	5.841 (1.732)	4.686 (1.73)	4.776 (1.27)
R^2	0.279	0.167	0.276	0.401	0.278	0.197
F	6.574**	3.806	21.699*	11.372*	7.308**	13.968*
N	19	21	59	19	21	59

F2F: face-to-face; GPA: grade point average.
*Significant at 0.01.
**Significant at 0.05.

difference ($t = 0.937$, $p > 0.05$) in GPAs between the monitored testing group ($M = 2.68$, $SD = 0.475$) and unmonitored testing group ($M = 2.80$, $SD = 0.520$). To examine differences between the three types of course delivery modes (online, hybrid, and F2F), ANOVA was conducted, which also resulted in a finding of no significant difference in GPA between the three groups ($F = 2.545$; $p = 0.084$).

To explore the question of whether human capital variables (GPA, major, cumulative credit hours) explain a greater degree of variation in examination scores when testing is monitored, several ordinary least squares (OLS) regressions were conducted using all the variables in the study. The results indicated that GPA was the only substantive explanatory variable, and F-tests indicated that the other variables were not statistically significant. Therefore, the simplest specifications are reported in Tables 2 and 3.

As indicated in Table 2, GPA was a significant predictor of mid-term examination scores for both types of testing groups (monitored, $F = 21.699$, $p = 0.01$; unmonitored, $F = 10.353$, $p = 0.01$) and final examination scores for both types of testing groups (monitored, $F = 13.969$, $p = 0.01$; unmonitored, $F = 18.826$, $p = 0.01$). ANOVA indicated that the R^2 statistic explained only slightly more variation for the monitored testing group (0.276) compared to the unmonitored testing group (0.214) for the mid-term examinations. However, for the final examinations, the R^2 results were

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just the opposite. R^2 explained substantially less variation in the final examination scores for the monitored testing group (0.197), compared to the unmonitored testing group (0.331). The relationship between GPA and examination scores was then explored across course delivery modes (online, hybrid, and F2F).

As indicated in Table 3, GPA was a significant predictor of mid-term examinations, except for the hybrid course (online, $F = 6.574$, $p < 0.05$; hybrid, $F = 3.806$, $p > 0.05$; F2F, $F = 21.699$, $p < 0.01$). GPA was also a significant predictor of final examinations in all course delivery modes (online, $F = 11.372$, $p < 0.01$; hybrid, $F = 7.308$, $p < 0.01$; F2F, $F = 13.968$, $p < 0.01$). The R^2 for the mid-term examination in the online section, with unmonitored testing, was greater than any other course delivery mode (online, $R^2 = 0.279$; hybrid, $R^2 = 0.167$; F2F, $R^2 = 0.276$), as was the R^2 for the online, unmonitored, final examination (online, $R^2 = 0.401$; hybrid, $R^2 = 0.278$; F2F, $R^2 = 0.197$).

Conclusions and discussion

Since its inception, online education has been maligned for a variety of reasons and one of the more prominent criticisms has been the issue of academic dishonesty in online, unmonitored testing. Given the fact that, with each passing year, more and more universities are offering online courses, it is surprising that so few studies directly examine the question of integrity in online testing. The overall purpose of this study was to add to the relative dearth of information in this area by exploring the issue of whether students in online courses are more likely to engage in academic dishonesty and whether academically dishonest students are more likely to enroll in online courses. Based on the results in this study, students in online courses, with unmonitored testing, are no more likely to cheat on an examination than students in hybrid and F2F courses using monitored testing, nor are student with low GPAs more likely to enroll in online courses.

Harmon and Lambrinos (2008) was the first study to address academic integrity in online testing by using human capital variables to predict examination scores. Harmon and Lambrinos (2008) found GPA to be a better predictor of test scores in F2F courses with monitored testing and concluded that students in online courses, with unmonitored testing, were more likely to engage in academic dishonesty. Similar to Harmon and Lambrinos (2008), the findings in the current study indicated that GPA explains a notable amount of variation in examination scores. However, the findings in the current study are also inconsistent with those in Harmon and Lambrinos (2008). The results in the current study indicated that GPA explained a greater degree of variation for online, unmonitored testing when compared to the monitored testing in the hybrid and F2F courses. Thus, following the logic presented in Harmon and Lambrinos (2008), the lower R^2 for the F2F and hybrid sections in this study can be interpreted to mean that cheating was more likely to occur in those sections of the course, which seems unlikely. Additionally, GPA did not explain a significant amount of variation in test scores for the mid-term examination in the hybrid section of the course, with monitored testing. A few possible explanations for the discrepancies in findings between the two studies emerge. First, in this study, several precautions were taken with the online, unmonitored testing to reduce the potential for cheating (as previously discussed). Harmon and Lambrinos (2008) do not discuss whether precautions to limit cheating were taken with the online tests in their study. In addition, in this study, the instructor for all sections of the course was the same; Harmon and Lambrinos (2008) do not mention whether the courses in their study were taught by the same instructor, and having different instructors can explain different results in testing scores. Furthermore, the course sections in this study were all taken during the same semester, while the course sections in the Harmon and Lambrinos' (2008) study were taken a year apart, which discounts the potential influence of history effects. Another plausible explanation for the differences

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in study outcomes is that while the model used by Harmon and Lambrinos (2008) to predict cheating is intriguing, it may be incomplete, and it is possible that some variable other than GPA exerts a greater influence on course examination scores, such as grade inflation. Grade inflation has been a hot topic over the past decade. Grade inflation occurs when instructors assign a higher grade to a test/assignment than what was actually earned by the student.

Capitalizing on a critique of Yates and Beaudrie (2009), the current study also used examination scores as outcome measures (instead of course grades); however, despite the differences in outcome measures, the findings in this study were similar to those in Yates and Beaudrie (2009). In this study, there was no significant difference in final or mid-term examination scores between sections of the course using monitored testing and sections using unmonitored testing. Englander et al. (2011) also criticized the Yates and Beaudrie's (2009) study because the study did not consider students' GPAs. Englander et al. (2011) assert that because research has found an inverse relationship between GPA and academic dishonesty, students with lower GPAs may be more likely to enroll in online courses, since such courses provide opportunities to engage in academic dishonesty through unmonitored testing. However, the findings in this study did not support such a contention; GPA did not differ significantly between course delivery modes.

While this study certainly expands the limited research on integrity in online testing, it is not without limitations. First, the researcher and the instructor for the course sections were the same. Although it is not uncommon for the researcher and instructor to be one and the same in educational research, it can introduce bias into the study. Different results may have been obtained had the students been randomly assigned to the three sections of the course. Generalizations should be approached with caution given the small sample size. Future research should look at incorporating additional variables, which may influence test scores, into the equation used to predict cheating, controlling for grade inflation, and increasing sample size.

Clearly, there is ample opportunity for cheating across all types of course delivery modes, which has been demonstrated through decades of research. What has not been demonstrated through research is that academic dishonesty is more likely to occur in an online course, which makes the perpetual myth of the greater occurrence of cheating in online courses somewhat perplexing. Even more perplexing and somewhat ironic are arguments focusing on the inability to ensure that the online student taking an examination is the actual person enrolled in the course, when, for decades, F2F instructors have given take-home essay examinations without concern being so commonly expressed. Perhaps it has been fear of technology which has propelled the myth of greater occurrence of cheating in online courses into reality and lack of familiarity with technology has served to breed contempt for online courses. As previously discussed, research has found that instructors who have not experienced online teaching are more likely than experienced online instructors to believe that more cheating occurs in online courses (McNabb and Olmstead, 2009; Yates and Beaudrie, 2009). This difference in opinion between the experienced and inexperienced online instructors may stem from the additional knowledge online instructors have regarding methods to ensure academic integrity.

The advent of online courses has prompted several suggestions for reducing academic dishonesty in online courses. For example, providing an educational environment that promotes academic integrity and raises awareness about what constitutes appropriate and inappropriate academic behavior, which can be accomplished by listing university policies and penalties for inappropriate academic behavior in the syllabus or in an online course announcement posting (Chiesl, 2007; WCET Briefing Paper, 2008). Academic dishonesty may be reduced by posting course learning objectives and listing the exact requirements for obtaining a specific grade (Chiesl, 2007). Opportunities for academic dishonesty may also be reduce by having a greater reliance on written assignments (WCET Briefing Paper, 2008) and use of plagiarism detection software, such as

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Turnitin, for written assignments (Chiesl, 2007; WCET Briefing Paper, 2008). Additionally, when using objective online tests, academic dishonesty may be reduced by preparing test banks and randomizing test questions so that each student receives a similar, but different set of test questions; presenting test questions one at a time, to prevent tests from being copied; not allowing backtracking during testing, to help prevent looking-up answers; having several tests, since students may be less likely to get help with cheating with several tests; and set a low point value for each test (Chiesl, 2007). Finally, to reduce opportunities for using unauthorized notes, tests may be timed, set to automatically submit when the allotted time expires and browsers disabled during testing (WCET Briefing Paper, 2008).

Perhaps one of the most effective ways to address anecdotal attacks on the integrity of online courses is to use identity verification techniques. For example, Secureexam Remote Proctor scans fingerprints and captures a 360° view around the online test taker (Dunn et al., 2010; Fontaine, 2012; WCET Briefing Paper, 2008) and can be purchased for approximately US$150 through the university bookstore (WCET Briefing Paper, 2008). Another verification technique is Webassessor, which lets human proctors watch online test takers remotely on Web cameras and listen to their keystrokes (Fontaine, 2012).

It is unfortunate that academic dishonesty has been, and no doubt will continue to be, the bane of educators. It is perhaps even more unfortunate that a barrier "to faculty acceptance of online teaching and learning is a concern about cheating" (Raines et al., 2011: 80), when there simply seems to be no convincing empirical evidence to support such a concern. Until such evidence is provided, perhaps it is time to move beyond seemingly unproductive discussions of which type of student (online or traditional) is most likely to cheat and engage in constructive conversations on how to improve academic integrity through pedagogical practices across course delivery modes.

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