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EMPIRICAL RESEARCH

A Conceptual Framework for Detecting Cheating in Online and Take-Home Exams

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ABSTRACT

Selecting the right methodology to use for detecting cheating in online exams requires considerable time and effort due to a wide variety of scholarly publications on academic dishonesty in online education. This article offers a cheating detection framework that can serve as a guideline for conducting cheating studies. The necessary theories and related statistical models are arranged into three phases/sections within the framework to allow cheating studies to be completed in a sufficiently quick and precise manner. This cheating detection framework includes commonly used models in each phase and addresses the collection and analysis of the needed data. The model's level of complexity ascends progressively from a graphical representation of data and descriptive statistical models to more advanced inferential statistics, correlation analysis, regression analysis, and the optional comparison method and the Goldfeld-Quandt Test for heteroskedasticity. An instructor receiving positive results on the possibility of cheating in Phases 1 or 2 can avoid using more advanced models in Phase 3. Tests conducted on sample courses showed that models in Phases 1 and 2 of the proposed framework provided results effectively for over 70% of the test groups, saving users further time and effort. High-tech systems and low-cost recommendations that can mitigate cheating are discussed. This framework will be beneficial in guiding instructors who are converting from the traditionally proctored in-class exam to a take-home or online exam without authentication or proctoring. In addition, it can serve as a powerful deterrent that will alleviate the concerns that an institution's stakeholders might have about the reliability of their programs.

Subject Areas: Cheating Detection Framework, Cheating Mitigation, Descriptive and Inferential Statistical Modeling, Goldfeld-Quandt Test, Online Exam Cheating, Take-Home Exam Cheating.

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INTRODUCTION AND BACKGROUND

Academic degrees conferred by institutions of higher education are generally based on the student performance displayed for a set of required courses. Exams are commonly used to evaluate this performance, and relevant grades are assigned. Stellar grades are a passport to upward mobility, so there can be considerable pressure placed on students to achieve higher exam scores through cheating (McCabe, Treviño, & Butterfield, 2001). University administrators and faculty are concerned about academic dishonesty, as the practice undermines the academic integrity of the degrees that schools offer their students (Barron & Crooks, 2005; Faurer, 2013; Hemming, 2010; Lanier, 2006). It is crucial that faculty conduct their exams under strictly controlled measures to ensure that all students actually earn the grade that reflects their true level of performance (Cluskey, Ehlen, & Raiborn, 2011; McCabe et al., 2001; Olt, 2002).

The University of Colorado at Denver and its College of Liberal Arts and Science (CLAS) considers cheating to be academic dishonesty that "involves the possession, communication, or use of information, materials, notes, study aids, or other devices not authorized by the instructor in an academic exercise, or (in) communication with another person during such an exercise" (CLAS, 2016, p. 1). Although there appears to be a difference between the definition of cheating and actual academic dishonesty, both terms appear regularly in the literature and are used interchangeably in this article.

Cheating Detection in Proctored and Unproctored Exams

Cheating that occurs in proctored in-class exams as well as unproctored online exams has been studied widely in the last decade and is well documented in the literature (Harmon & Lambrinos, 2008; Hemming, 2010; Hollister & Berenson, 2009; McCabe et al., 2001; Olt, 2002; Shon, 2006). The general perception is that unproctored online exams will demonstrate higher incidences of cheating (Kennedy, Nowak, Raghuraman, Thomas, & Davis, 2000; King, Guyette, & Piotrowski, 2009). Nearly 75% of accounting students that were surveyed at a university in Florida perceive that it is easier to cheat in an online exam than in a proctored in-class exam (King et al., 2009).

Studies on cheating have been carried out using surveys and/or interviews with students (Bowers, 1964; McCabe et al., 2001). However, a survey faces the challenges of coverage, measurement, nonresponse, or incorrect responses (deLeeuw, Hox, & Dillman, 2008). Due to these issues, results of studies that have used surveys to examine cheating behavior must be interpreted carefully (Fask, Englander, & Wang, 2014). Indeed, few students will want to admit to cheating, even when completing anonymous self-reporting surveys. This assertion is supported by results from an anonymous self-reporting survey conducted for this article. Approximately 100 surveys were distributed to students, and 77 of them were completed and returned. Among those returning the survey, 13% agreed and 4% strongly agreed that cheating took place in their online exams. In contrast, a larger number of students disagreed (40%) and strongly disagreed (19%) that cheating took place. Due to these documented problems and the higher cost involved in carrying out surveys, more researchers are moving toward empirical methods to study the nature and incidence of cheating (Fask, Englander, & Wang, 2015; Harmon & Lambrinos, 2008; Hollister & Berenson, 2009).

Cheating in online exams is usually detected by using self-reporting surveys, empirical methods, and a combination of quantitative and qualitative methods. However, results from earlier studies are mixed. Some studies have reported cheating (Fask et al., 2015; Harmon & Lambrinos, 2008; King et al., 2009) while others registered no cheating (Greenberg et al., 2009; Hollister & Berenson, 2009; Peng, 2007; Werhner, 2010). Shen, Chung, Challis, and Cheung (2007) found no significant performance difference between the traditional classes and online classes, although the traditional class performed slightly better than the online class.

Academic dishonesty has been studied under different exam-course settings, including: (1) unproctored online (OL) exams in online (OL) courses (Hollister & Berenson, 2009; King et al., 2009); (2) proctored in-class (IC) exams in OL courses (Hollister & Berenson, 2009; Werhner, 2010); (3) proctored IC exams in traditional IC courses (Shon, 2006); (4) unproctored take-home (TH) exams in IC courses (Andrada & Linden, 1993; Marsh, 1984); and (5) OL exams or quizzes in IC courses (Fask et al., 2015; Peng, 2007). This study consisted of OL exams in IC courses and TH exams in IC courses.

Cheating Detection Empirical Models

Previous empirical studies applied a variety of tools ranging from simple graphical and descriptive statistical models to more advanced inferential statistics, analysis of variance (ANOVA), correlation, regression analysis, the Goldfeld-Quandt Test (GQT) for heteroskedasticity, and comparison of predicted with observed exam scores (Harmon & Lambrinos, 2008).

Cheating detection begins with the application of a plain two-dimensional graph and descriptive statistics. These are essential for establishing a visual understanding of the concept and identifying patterns without stringent assumptions, as in the case with statistical models. Graphs are used by researchers to organize raw unorganized data into a form that can be presented or used as inputs into statistical models. They are often used singly or in combination with the other statistical models to compare scores on proctored in-class and online exams and to compute the mean and standard deviation of the test parameters. Extensive use of summary statistics to analyze students' performance measures and self-admitted responses to cheating have been used by many researchers, including McCabe et al. (2001); Harmon and Lambrinos (2008); Hollister and Berenson (2009); and Dobkin, Gil, and Marion (2010). In addition to simple graphs (e.g., frequency polygons, and line graphs), this article introduces a graphical cheating indicator to check whether the differences in the mean sample scores of online and in-class exams were due to cheating or something else. This is discussed later in the article.

Researchers have extensively applied hypothesis testing to determine if cheating took place in online exams by comparing if there is a significant difference in the scores of an OL unproctored and IC proctored exam score (Fask et al., 2015; Harmon & Lambrinos, 2008; Hollister & Berenson, 2009; Peng, 2007; Werhner, 2010). If the exam scores between OL and IC or TH and IC are significantly different, then the differences denote that chance causes can be ruled out and we can conclude that cheating may have taken place. Due to relatively small sample sizes, sometimes less than 30, these researchers have used the student *t*-test for the hypothesis test.

More advanced correlational and regression analysis models have also been applied to detect cheating. An approach presented by Harmon and Lambrinos (2008) utilized correlation and regression analysis as well as variance analysis to detect cheating in an online macroeconomics exam. A regression model was used to predict their summer 2004 and summer 2005 final exam scores from student-related explanatory variables. According to Harmon and Lambrinos (2008, p. 119), "the courses, although offered a year apart, were almost identical in structure and content." Among several variables that were considered by Harmon and Lambrinos (2008), GPA was the only significant variable that reflected a student's ability. Moreover, they reasoned that the independent "human capital variable such as GPA" has a high relationship (coefficient of determination, R^2) to the dependent variable (exam scores) due to the student's high performance in the proctored in-class exam, rather than to cheating (Harmon & Lambrinos, 2008, p. 121). Cheating would result in a low value for R^2. Similarly, Fask et al. (2015, p. 2) introduce student GPA and class attendance as "mastery (independent) variables" that could reasonably increase the performance of the student and correspondingly detect if cheating has occurred.

The OPM 450 and OPM 350 courses offered in academic years 2014-2015 and 2015-2016 were a part of this study. Missed class days (excused or unexcused) and percentage of assignments submitted up to the exam date are considered as independent variables that are responsible for the students' high in-class exam scores (dependent variable). Due to privacy concerns, student GPA was not included as an independent variable, although it is highly related to student performance and was considered by other researchers (e.g., Fask et al., 2015; Harmon & Lambrinos, 2008).

The GQT proposed by Goldfeld and Quandt (1965) for testing homoscedasticity was adapted to test for heteroskedasticity (unequal variance). It is used by researchers to detect online cheating by examining the variance (σ^2) of the residual errors (ε_i) from the regression models (Fask et al., 2015; Harmon & Lambrinos, 2008). The limitations of the GQT are discussed in more detail in the Conclusions and Limitations section. Furthermore, comparison of the predicted mean values with the observed values obtained from the regression model is an additional method to detect cheating (Harmon & Lambrinos, 2008).

These statistical models can indicate the possibility of cheating or no cheating in an objective exam. It is difficult to identify and prove that specific students have cheated based on statistical models (Marx & Longer, 1986). Alerted instructors can increase proctoring and can keep a closer observation of the students, change the exam schedule, modify the exam format, and use other interventions provided in the Interventions for Mitigating Cheating section of this article.

Proposed Study

A large number of researchers drawn to this field have generated a wide variety of scholarly efforts on the academic dishonesty occurring in online exams. Therefore, an instructor who is planning a cheating study will spend considerable time and effort searching for the most relevant methodology. There is an urgent need for a preplanned and well-organized procedure for instructors and researchers to use in detecting cheating in online or on other unproctored exams (e.g., take-home exams).

This article provides a conceptual framework for planning and organizing a sustained cheating detection and mitigating program. The framework emphasizes the standard means of cheating detection using related concepts from the auditing profession. Cheating in academics is similar to financial fraud that is detected during the audit of a company's financial statements by trained auditors. The "fraud triangle" discussed by Ramos (2003, p. 28) is the conceptual framework used as a guide in detecting financial fraud that satisfies one or more of the three conditions (incentive/pressure, opportunity, and rationalization/attitude) when fraud occurs. Subsequently, Becker, Connolly, Lentz, and Morrison (2011) matched the three sides of the "fraud triangle" (Incentive to cheat, an opportunity to cheat, and rationalization to cheat) with cheating in academics, producing the business fraud triangle that they used as a framework to uncover academic dishonesty among business students. The tested business fraud triangle (Becker et al., 2011) has been adopted as the conceptual framework for the cheating detection framework (CDF).

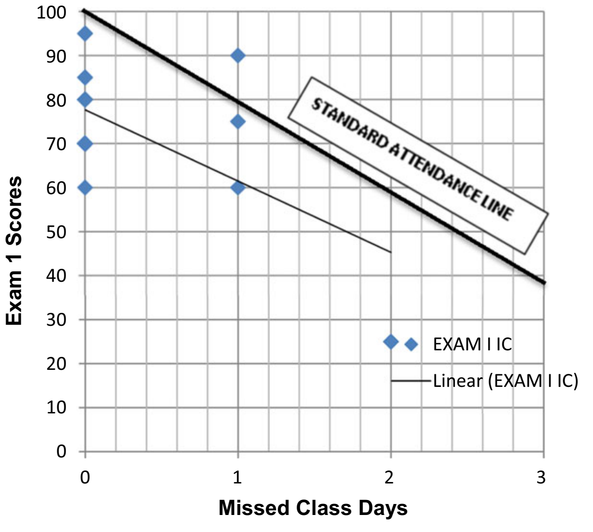
The conceptualization of the framework occurred during the investigations into alleged cheating complaints about online exams at a mid-size university in the Commonwealth of Virginia and included an extensive literature review. The necessary assumptions, theories, and related graphical and statistical models are arranged in three phases/sections within the main body of the framework, allowing cheating studies to be completed in a sufficiently quick and precise manner. The framework offers instructors the choice of commonly used graphical charts and statistical models to select in each phase and addresses the collection and analysis of necessary data. Tests conducted during this study on sample business management courses showed that the proposed CDF was able to detect cheating in Phases 1 and 2 for over 70% of the test groups, thus saving users further time and effort.

CHEATING DETECTION FRAMEWORK CONCEPTUALIZATION

Study Justification

The OPM 450: Operations Management and the OPM 350: Transportation and Logistics Management undergraduate courses under study had been taught in face-to-face classes during the past, with proctored in-class exams for the former and take-home exams for the latter. The course codes and names published in this study were altered to safeguard the department's privacy policies. In fall 2015, a decision was made to continue with IC courses but to administer all assignments and three out of the four exams OL using the Blackboard Course Management platform. It is estimated that this technological approach saves almost five classes or more than ten percent of the class meetings in a regular semester. This savings in "seat time" (Peng 2007, p. 10) allows the instructor to cover extra course material. The OL exams provide flexibility for traveling students, especially athletes who can take the online exams at any time or place. It also gives more time for faculty

Figure 1: Attendance plot for in-class Exam 1.

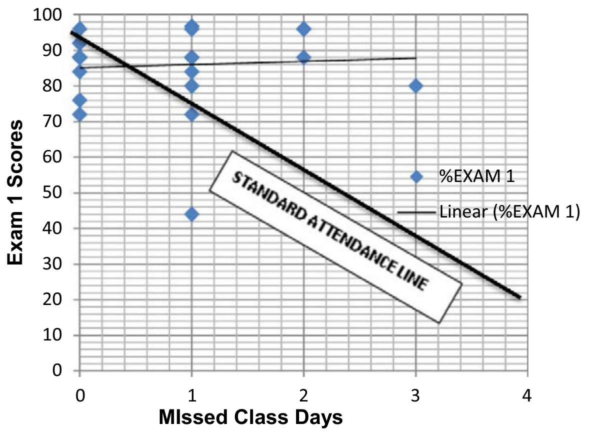


to extend their office hours for advising students and to pursue their scholarly activities.

The rationale for the conceptual framework offered in the present study was the sudden rise in exam scores for the OPM 450 course when these exams were transformed from proctored in-class exams to online exams given no proctors. According to Siegmann, Moore, and Aquino (2014), higher scores in online exams could be due to more time being available for instructor-student interactions, a less stress-filled exam environment, flexible timing, and students doing more reading for unknown answers. These findings were supported by results from the anonymous self-reporting survey addressed in the Introduction and Background section, based on students who completed the OPM 450 and OPM 350 online exams. Among those students that participated in the survey, 66% expressed a preference for online exams because of the flexible timing to complete their exams (77%), and their ability to take the exam when fully prepared (95%).

In this study, the instructor suspected that the higher online exam scores for OPM 450 were due to cheating because students with poor attendance records were getting abnormally high exam scores. This outcome contradicted results of Dobkin et al. (2010), which reported that attendance at class meetings has a positive impact on exam performance. The attendance plots graphed in Figures 1 and 2 for OPM 450 proctored in-class exams and unproctored online exams, respectively, visibly demonstrate the impact of attendance on the scores for both exams. Figure 1 shows a general pattern of proctored in-class exam scores that realistically decreases almost identically with the standard attendance line (negative slope) when class days missed increases, hence supporting the results of Dobkin et al. (2010). Figure 2 shows the pattern of online exam scores in comparison to a standard attendance line. The exam scores increase (positive slope) unrealistically as the

Figure 2: Attendance plot for online Exam 1.



corresponding number of missed class days increase, suggesting the possibility of cheating.

Study Design

The development and testing of the cheating detection framework (CDF) were conducted in two parts. In Part 1, each phase of the CDF was assigned appropriate graphical representation and statistical models in ascending order of complexity. In Part 2, the functionality of the framework was tested on groups of sample business courses. A group consisted of an in-class (IC) or take-home (TH) exam given in the fall 2014 or spring 2015 semester of an academic year and an online (OL) exam given during the same semester of the following academic year (i.e., fall 2015 and spring 2016).

A total of seven groups were used in Parts 1 and 2 of this study. Group 1 was used in Part 1 to illustrate the composition and working of the framework, and Groups 2-7 were similarly organized and were used to test the framework in Part 2. A detailed composition of all seven groupings is provided in later sections (Table 3).

The equivalence requirements for assignments, quizzes, and exams suggested by Fask et al. (2014) were strongly enforced within the time, costs, and legal restraints. The seven groups, each containing a set of two examinations, had a mix of students from across campus. The OPM 450 course was a Management major requirement, but it was popular in other departments across campus. Every semester, the study population consisted of primarily senior level undergraduate students with a management major or minor from departments including architecture, aviation, journalism and mass media, psychology, and others. Similarly, OPM 350 was populated by juniors from management, aviation, and other students seeking a major or minor in management. Random registration for these courses across campus resulted in a class of students with approximately similar characteristics every semester. The OPM 450 and 350 courses were taught by the same professor using an identical syllabus, textbook and notes, PowerPoint presentations, exam format (with different questions), and assignments in each course. The OL and IC exams consisted of multiple-choice, true/false, and fill-in-the-blank questions, which could be graded by Blackboard Course Management Systems. The difficulty level of questions was maintained the same in both exams but the wording and parameters were slightly modified to get different answers.

To maintain a consistent computer grading system, there is a need for objective-type questions consisting of a mix of multiple-choice, true/false, and fill-in-the-blank questions. The smaller descriptive quantitative and qualitative questions can be included by breaking the question into subquestions whose answers are sequentially entered into the course website in precise single or multiple numerical value(s) or word(s). For the larger qualitative essay questions, it is highly recommended that instructors use an anti-plagiarism tool to detect cheating.

Part 1: Development of the Cheating Detection Framework (CDF)

Group 1, consisting of Exam 1 scores for the fall 2014 OPM 450 proctored IC exam and fall 2015 OPM 450 OL exam, was used to illustrate the development and operation of the three-phase CDF. (Refer to Figure 3.)

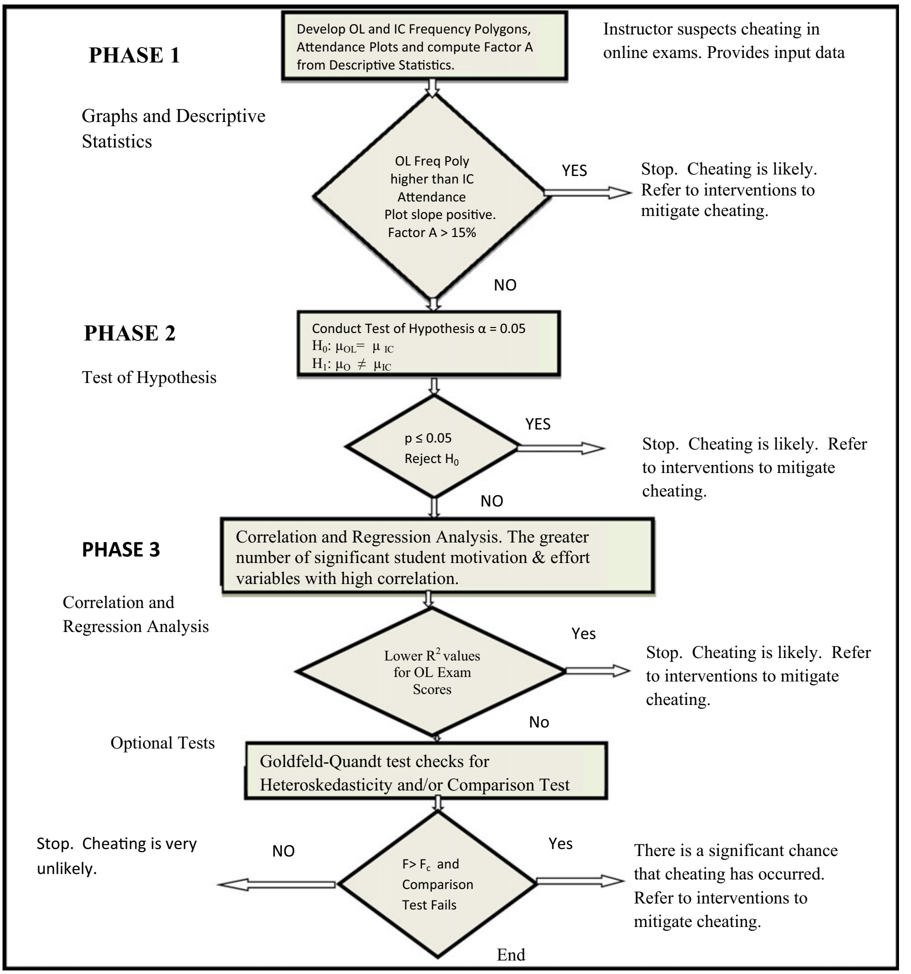
Each phase of the CDF is discussed separately in the following subsections.

Phase 1: Preliminary tests

Exam 1 scores and attendance records were used as inputs for developing the graphical charts and descriptive statistics models. An examination of the attendance plots of both OPM exams in Figure 1 and 2 generally shows that OL students with poor attendance were scoring higher on their exams, contradicting the results of Dobkin et al. (2010). The height of the OL exam scores' frequency polygon in Figure 4 was substantially higher compared to the IC exam scores. This was just a visual observation of the frequency polygon and line graphs. The Chi-square goodness of fit test (Pett, 2016) could have been used to determine if the differing size of the frequency distributions for the OL and IC or TH data sets were significantly different or just due to chance. Instead, a simple graphical cheating indicator displayed in Figure 5, together with descriptive statistics, was used as an alternative. This cheating indicator displays the relationship between the percentage of difference between the OL and IC mean scores (factor A) and the p value (probability) from the test of hypothesis. The p value at which the decision switches from "no cheating" to "cheating" was set at $p = .06$ (a little over the .05 level), which corresponded to the base factor A value of 15%. In the case of Group 1, which is being discussed here, the factor A value for the mean OL and IC exam scores (86 and 72) was 19%, which falls in the cheating zone.

Therefore, based on the positive slope results from the attendance plots in Figure 2, the height of the OL frequency polygons (Figure 4), and results from the cheating indicator graph (Figure 5), Phase 1 of the CDF suggests that cheating is strongly possible. It is recommended that the movement to higher phases of the CDF be stopped and a cheating mitigating strategy be implemented, as discussed later. Although it is not necessary to go to the next phase, an instructor may decide to move to Phase 2 to confirm the results from Phase 1 and conduct further analysis.

Figure 3: Schematic outline of the cheating detection framework (CDF).



Phase 2: Testing at the significance level

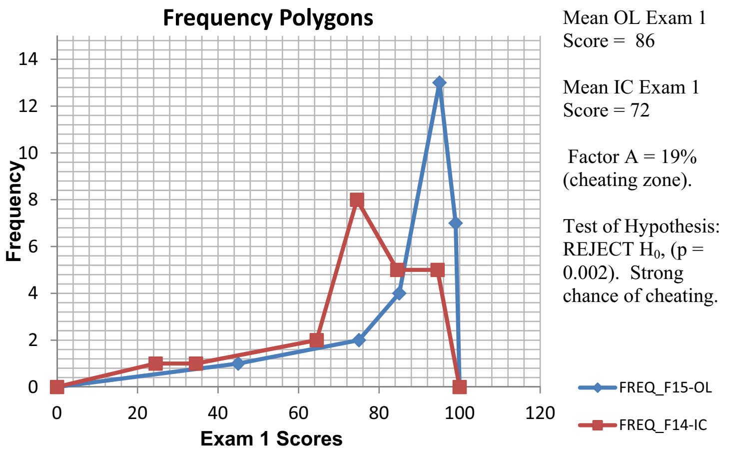
In Phase 2, the hypothesis test is recommended to investigate whether the mean scores in OL and IC exams are the same or significantly different. The null and alternate hypothesis is described as

$$H_0 : \mu_{OL} = \mu_{IC},$$

$$H_1 : \mu_{OL} \neq \mu_{IC}.$$

The level of significance denoted by α must be kept as small as possible to reduce the probability of rejecting the null when it is true, a Type I error, which is equivalent to stating that cheating takes place when it really does not take place. The values of α used in research are generally, $\alpha = .001$, .01, and .05. The value of $\alpha = .05$ is commonly used in this type of study, and some software packages apply

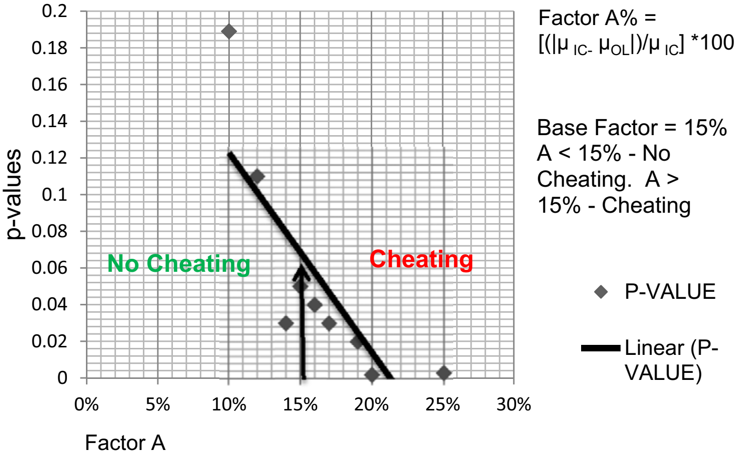
Figure 4: Phase 1 graphical method for Group 1.



the .05 value by default. The *t*-test for two sample means with unequal variance is run on the data and the computed *t*-value is subject to the following decision rule (α: = .05, two-tailed):

If $t < t_c$ or $-t < -t_c$ or if $p < .05$, the null is rejected, and the alternate hypothesis is supported. (The t_c value in the criterion corresponds to the critical value associated with the degrees of freedom and the chosen α level.) In the Group 1 case, $t = -3.37$, $t_{.05,\,35} = -2.03$, $p = .0019$. Therefore, the null hypothesis is rejected, and we conclude that the mean scores in OL and IC exams were significantly different. With the mean OL exam score being higher, we conclude that cheating

Figure 5: Cheating indicator.



took place in the OL exams. Based on the framework, it is recommended that the study is stopped and the instructor plan strategies for mitigating cheating. Although unnecessary, some instructors may opt to proceed to Phase 3 to reconfirm the results from Phase 2.

Phase 3: Advanced statistical models

In Phase 3, cheating is detected by examining the multiple regression results for each exam score within the group. The three independent variables included in this study were attendance, assignments completed, and student gender. Class attendance and submission of self-completed assignments were performance-associated independent variables that were strongly related to the dependent variable (exam scores). Gender was also included since the authors intended to test the finding by researchers that cheating among women is on the rise (McCabe et al., 2001). A cumulative GPA of each student and other performance-related independent variables were not included in this study but can be added if readily available.

Two multiple regression models developed for Group 1's exam scores are presented in the following equations (1) and (2). The dependent variable Y_{ij} measures the total contribution of the three independent variables, where index "i" = 1, 2, 3, …, nth student. The index "j" = OL or IC exam.

$$\begin{aligned} Y_{i,OL} = {} & \beta_{0,OL} + \beta_{1,OL}\left(GENDER_{i,OL}\right) \\ & + \beta_{2,OL}\left(ABS_{i,OL}\right) + \beta_{3,OL}\left(ASSIGN_{i,OL}\right), \end{aligned} \tag{1}$$

$$\begin{aligned} Y_{i,IC} = {} & \beta'_{0,IC} + \beta'_{1,IC}\left(GENDER_{i,IC}\right) \\ & + \beta'_{2,IC}\left(ABS_{i,IC}\right) + \beta'_{3,IC}\left(ASSIGN_{i,IC}\right). \end{aligned} \tag{2}$$

where $Y_{i,OL}$ is score for student "i" in online Exam 1; $GENDER_{i,\ OL}$ is gender of student "i" in OL Exam 1 (1 = male, 0 = female); $ABS_{i,\ OL}$ is number of days student "i" absent (excused and unexcused) from the class up to Exam 1; $ASSIGN_{i,\ OL}$ is average percentage of assignments completed by student "i" up to OL Exam 1; $Y_{i,\ IC}$ is score for student "i" in proctored IC Exam 1; $GENDER_{i,\ IC}$ is gender of student "i" in proctored IC Exam 1 (1 = male, 0 = female); $ABS_{i,\ IC}$ is number of days student "i" absent from class up to Exam 1 (excused and unexcused); and $ASSIGN_{i,\ IC}$ is average percent (%) of assignments completed by student "i" up to IC Exam 1.

To improve the linearity, equations (1) and (2) are transformed into natural log-linear (LN) models (Murray, 2006) as follows:

$$\begin{aligned} LN\left(Y_{i,OL}\right) = {} & \beta_{0,OL} + \beta_{1,OL}\left(GENDER_{i,OL}\right) \\ & + \beta_{2,OL}\left(ABS_{i,OL}\right) + \beta_{3,OL}\left(ASSIGN_{i,OL}\right), \end{aligned} \tag{3}$$

$$\begin{aligned} LN\left(Y_{i,IC}\right) = {} & \beta'_{0,IC} + \beta'_{1,IC}\left(GENDER_{i,IC}\right) \\ & + \beta'_{2,IC}\left(ABS_{i,IC}\right) + \beta'_{3,IC}\left(ASSIGN_{i,IC}\right). \end{aligned} \tag{4}$$

The summarized results of the linear regression analysis are shown in Table 1. The fitted linear regression equation (5) for IC exams had one significant

Table 1: Results of the multiple regression Equations (3) and (4) (Group 1).

Multiple Regression	Intercept	Significant Variable (S)	R	R^2	F Ratio	F Sig	N
Equation (3) (OL)	4.3776	None	.134	.018	.139	.936	21
Equation (4) (IC)	4.6656	$\beta'_{2,\ IC} = 0.361^{**}$	.694	.481	5.251	.01	27

$^{**}p < .01$

Table 2: Goldfeld-Quandt Test (GQT) for heteroskedasticity (Group 1).

Multiple Regression	Measure of Variance	df	SSR	SSR/df	F Ratio	F*c* $\alpha = .05$
Equation (3) (OL)	Residuals	23	.635	.028	$F = .046/.0280 = 1.64$	$F_{17,23} = 2.091$ Do Not Reject H_0
Equation (4) (IC)	Residuals	17	.777	.046		

independent variable while the linear regression for OL exams had no significant variables.

$$LN\left(Y_{i,IC}\right) = 4.6655 - 0.3611\left(ABS_{i,IC}\right). \tag{5}$$

The value of R^2 is low (1.8%) for the OL exam scores and is high (48.1%) for the IC exam scores. Attendance (ABS) was the only significant variable for the IC exam scores (equation (4)), accounting for approximately 48% of the variation, while the other independent variables were not significant. Equation (3) had no significant variables. Therefore, none of the independent variables in the regression model for equation (3) contributed toward the approximate 2% of the variation. This large difference in the value of R^2 between OL and IC is because the performance associated variable ABS contributed to this increase in R^2 in the proctored IC exam, while a low value in the OL exam showed the same variable as having a low contribution (Fask et al., 2015; Harmon & Lambrinos, 2008). Hence, the possibility of cheating in the OL exams was significantly higher than cheating in the proctored IC exams, which were under strict supervision.

Optional test

The CDF contains two optional tests for cheating detection. They are not a requirement but can be used by instructors desiring additional confirmation of the outputs from Phases 1, 2, and 3, or who may have skipped some of the phases in favor of the other options.

The first is the GQT for homoscedasticity, used to test for heteroskedasticity or the presence of unequal variance. The homoscedasticity assumption for the regression model requires that the disturbances or errors (ε_i) are constant and randomly distributed, producing constant variance (σ^2). This concept has been used to study disturbances in two independent samples, for example, the OL and IC exam scores. The GQT tested the multiple regression equations (3) and (4) for differences in variance, which is termed as the test of heteroskedasticity. The question, however, is: *Do the error terms ε_i for equation (3) and (4) have a different variance for OL and IC exam scores?*

The following steps in applying the GQT are suggested by Murray (2006):

i. Create two discrete sets. Set 1 consisted of $n_{OL} = 27$ students in the OL Exam 1, and Set 2 consisted of $n_{IC} = 21$ students in the proctored IC Exam 1.
ii. State the null and alternate hypothesis.

$$\mathrm{H}_0 \colon = \sigma^2{}_{OL} = \sigma^2{}_{\mathrm{IC}},$$

$$H_1 = \sigma^2{}_{OL} \neq \sigma^2{}_{\mathrm{IC}}.$$

iii. Regress the natural log-linear regression for equations (3) and (4).
iv. Compute the F ratio of the sum of squares of the residuals (SSR) for OL and IC (Table 2).
v. Compare the F ratio with the critical value F_c at $\alpha = .05$. If F ratio $> F_c$, the null hypothesis is rejected.

The computed values are F ratio $= 1.640$ and $F_{17,\,23} = 2.091$. Since, F ratio $< F_{17,\,23}$, there is not enough statistical evidence to reject the null hypothesis, and we can conclude that there is no difference in the variance between the OL exams and the proctored IC exams. This result satisfies the homoscedasticity assumption for regression models and concludes that it is unlikely cheating is taking place. However, this result from this optional test differs from the results from Phases 1, 2, and 3.

The second optional test is a comparison test that was conducted to corroborate the Phase 1, 2, and 3 results. The observed performance associated variable, $ABS_{i,j}$ values for OL and IC, were input into linear regression equation (5) to compute the predicted exam scores, which were then compared with the observed exam scores for OL and IC students. The difference between the predicted OL (70.5) and observed (86.1) scores was highly significant ($p = $ 1.57E-07). In contrast, the difference between the predicted IC (75.1) and observed (71.2) scores was not significant ($p = .3897$). Hence, results of a comparison test confirm the presence of cheating in the OL exams.

Although cheating could have been detected in the earlier Phases 1 and 2, all the Phases 1, 2, and 3 along with the optional models were applied to demonstrate the different models that instructors can use, the data needed for testing, and interpretation of the results.

Part 2: Testing the Framework

The cheating detection capabilities of the framework were tested on seven groups (four being OPM 450 and three for OPM 350). The test results for all the groups involved in the development and testing of the CDF are summarized in Table 3.

Due to space limitations, only the testing results for Group 3 (OPM 450) and Group 6 (OPM 350) are documented here, in detail.

Group 3 was subjected to testing by graphs and descriptive statistical models in Phase 1. The frequency polygons indicate the highest point was the IC exam conducted in spring of 2015. The computed mean scores for OL (75) and IC (71) exams indicated a marginal difference of 6% (factor A) which, according to the cheating indicator shown in Figure 5, falls in the "no cheating" zone. In the case of Group 3, one concludes that there was no cheating in the OL exams. However, the attendance plots for the OL exams shows a positive slope which can be due to cheating. Therefore the instructor is advised to move to Phase 2 to confirm that no cheating is taking place. The hypothesis test did not reject the null hypothesis ($p = .290$). There is no significant difference in exam scores which leads one to conclude that there is no strong evidence to prove that cheating is taking place. No cheating was detected in Phase 2, so further testing in Phase 3 may be discontinued. The CDF prepares a test report card for the instructor of Group 3 providing details of tests conducted in Phases 1 and 2. A sample of this test report card is shown in Figure 6 for Group 6, which is discussed in the following paragraphs.

In Group 6, the CDF's results were inconsistent for the phases. In Phase 1, the highest peak of the frequency polygon was for the OL exam (Figure 6). The attendance plots for both exam scores had a positive slope. The attendance plot for TH exam that is displayed in Figure 6 had a greater positive slope than the OL exam. The mean exam scores of 78 in the OL exams and 85 in the TH exam were close with factor A = 9%. For this value of Factor A, the cheating indicator (Figure 5) classified Group 3 under the "no cheating" zone. In Phase 2, the test of the hypothesis was modified to include the TH exam in place of the IC exam, as follows:

$$H_0 : \mu_{OL} = \mu_{TH},$$

$$H_1 : \mu_{OL} \neq \mu_{TH}.$$

The computed $p = .0502$ was marginally greater than .0500. An instructor will be unclear about these borderline outcomes in Phases 1 and 2 and needs to proceed to Phase 3. In Phase 3, the multiple regressions equation (4) for IC exam were replaced by the equation (6) for the TH exam as follows:

$$\begin{aligned} LN\left(Y_{i,TH}\right) = {} & \beta'_{0,TH} + \beta'_{1,TH}\left(GENDER_{i,TH}\right) \\ & + \beta'_{2,TH}\left(ABS_{i,TH}\right) + \beta'_{3,TH}\left(ASSIGN_{i,ITH}\right). \end{aligned} \tag{6}$$

Equations (3) and (6) are applied to the OL and TH exams in Group 6. The multiple regression models' R^2 value for the TH exam scores of approximately 31% is higher than the R^2 value for the OL exam scores of approximately 11%, but there were no significant variables in either equation. Since none of the performance-associated independent variables in the regression model for equations (3) and (6) contributed toward the 31% and 11% of R^2, there were other non-explanatory factors that influenced the dependent variable, one of which was cheating. With TH having a higher R^2 than OL, it can be concluded that cheating took place in OL and TH exams, but cheating is higher in TH exams. Finally, the GQT provides

Table 3: Summarized test results for Groups (Gr) 1-7.

Gr	Course	Sem/Exam No.	Exam Type	Test Results	Cheating (Y/N/U)
1	OPM 450 OPM 450	Fall 2015/1 Fall 2014/1	OL IC	Phase 1: OL attend. plot positive slope. OL freq poly. Higher. Dist. Stat ($\mu_{OL} = 86 > \mu_{IC} = 72$). Factor A = 19%. Stop. Cheating detected. Phase 2, $p = .0019$. Reject H_0. Stop. Cheating detected. Phase 3, $R^2{}_{IC} > R^2{}_{OL}$ (.481, .018). GQT; $F = 1.64$ & $F_{17,\,23} = 2.091$. Do not reject H_0. Comp. Test, obs value of OL significant > pred. values ($p = 1.57\text{E-}07$). Cheating detected	Y
2	OPM 450 OPM 450	Fall 2015/3 Fall 2014/3	OL IC	Phase 1: OL attend. plot slightly positive slope. OL freq poly. Higher. Dist. Stat ($\mu_{OL} = 92 > \mu_{IC} = 79$). Factor A = 17%. Stop. Cheating detected. Phase 2, $p = .03$. Reject H_0. Stop. Cheating detected. Phase 3 N/A	Y
3	OPM 450 OPM 450	Spring 2016/1 Spring 2015/1	OL IC	Phase 1: OL attend. plot positive slope. OL freq poly. higher. Dist. Stat ($\mu_{OL} = 75 > \mu_{IC} = 71$). Factor A = 6%. Stop. Cheating not detected. Phase 2, $p = .290$. Do Not Reject H_0. Stop. No cheating detected. Phase 3 N/A	N
4	OPM 450 OPM 450	Spring 2015/3 Spring 2016/3	OL IC	Phase 1: OL attend. plot positive slope. OL freq poly. Higher. Dist. Stat ($\mu_{OL} = 82.1 \approx \mu_{IC} = 82.3$). Factor A = 0%. Stop. Cheating not detected. Phase 2, $p = .9565$. Do Not Reject H_0. Stop. No cheating detected. Phase 3 N/A	N
5	OPM 350 OPM 350	Fall 2014/2 Fall 2015/2	OL TH	Phase 1: TH attend plot positive slope. OL freq poly. Higher. Dist. Stat ($\mu_{TH} = 99 > \mu_{IC} = 75$). Factor A = 32%. Stop. Cheating detected. Phase 2, $p = .001$. Reject H_0. Stop. Cheating detected. Phase 3 N/A	Y

(Continued)

Table 3: *(Continued)*

Gr	Course	Sem/Exam No.	Exam Type	Test Results	Cheating (Y/N/U)
6	OPM 350 OPM 350	Spring 2016/1 Spring 2015/1	OL TH	Phase 1: OL and TH attend. plots both positive slopes. OL freq poly. higher. Dist. Stat ($\mu_{TH} = 85 > \mu_{OL} = 78$). Factor A = 9%. Undecided. Phase 2, $p =$ .0502. Undecided. Phase 3, $R^2{}_{TH} > R^2{}_{OL}$ (.31, .11). GQT; $F = 1.03$ & $F_{7,\,11} =$ 3.01. Do not reject H_0. No cheating detected.	U*
7	OPM 350 OPM 350	Spring 2016/3 Spring 2015/3	OL TH	Phase 1: TH attend. plot more positive. TH freq poly. Higher. Dist. Stat ($\mu_{TH} = 96 > \mu_{OL} = 66$). Factor A = 46%. Stop. Cheating detected. Phase 2, $p =$ 3.25E-08. Reject H_0. Stop. Cheating detected. Phase 3 N/A.	Y

*Undecided. The Instructor will make the final decision.

an F ratio = 1.03 and $F_{7,\,11} = 3.01$. The null hypothesis was not rejected, meaning there was no difference in the variations and hence, no cheating. The provision of inconsistent results indicates that the CDF has a limitation in such narrow or close cases and the instructor should make the final decision after a review of all the test results documented in the test report card (Figure 6).

The CDF could provide sufficient test results to assist an instructor in determining if cheating possibly took place or not for over 85% of the test groups. Cheating was detected in 67% of these test groups, while no cheating was detected in 33% of these test groups. Tests conducted on the groups showed that models in Phases 1 and 2 of the proposed framework provided results effectively for over 70% of the test groups, saving users further time and effort.

INTERVENTIONS FOR MITIGATING CHEATING

After detecting cheating in the unproctored OL and TH exams, it is the instructor's responsibility to take appropriate steps to avert or mitigate cheating. Further discussions in this section will concentrate on OL exams, although cheating was found to be higher in TH exams.

One major technical issue with OL exams is authentication regarding who is actually taking the OL exam. The other issue pertains to how are OL exams that are held at testing centers being proctored. Currently, Berkey and Halfond (2015) have identified vendors marketing advanced equipment and software for authentication and proctoring purposes. For example, ProctorU, Examity, and Software

Secure are vendors specialized in supplying and implementing authentication and proctoring services. There are fully automated systems such as ProctorTrack, marketed by Verificient Technologies; ProctorFree, in partnership with Blackboard and CANVAS; Proctorio; and Biometric Security Systems and Facial Recognition (BIOMIDS), which are capable of performing authentication and proctoring in the absence of any human proctors. The market for automated cheating alleviation systems is expected to grow as more institutions crack down on academic dishonesty (Berkey & Halfond, 2015).

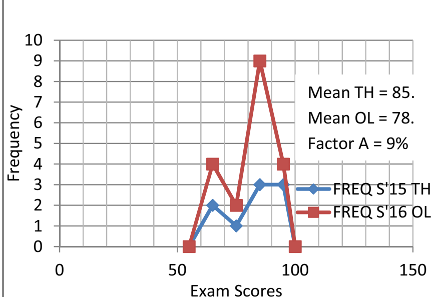
The above discussion has focused on high-tech applications to manage cheating in OL exams. These advanced systems can be expensive to implement and operate. There are pragmatic approaches that are easy to implement at low or no cost, especially if an institution uses Blackboard, CANVAS, or other Web-based course management systems.

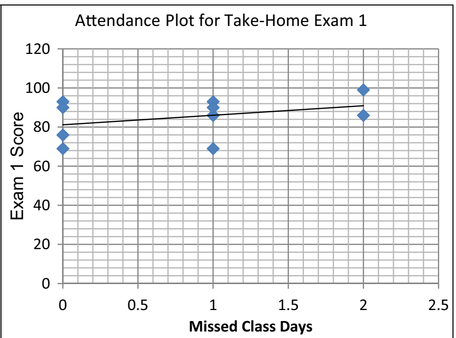
Figure 6: Test Report Card for Group 6.

Course: OPM 350_Exam 1 Semester/Year Spring/2016 – Spring 2015

Date: Prepared ________________.

Phase 1: Frequency Polygon





Phase 2: Test of Hypothesis: Decision Rule (α: = 0.05, two-tailed). If $t < t_c$ or $-t < -t_c$ the null is rejected and the alternate holds true. $t = 2.019$, $t_c = 2.093$, $p = 0.0502$ Borderline Case

Phase 3: Results of the regression models for Equations 3 and 6

Regress/Exam	Intercept	Significant Variable (S)	R	R^2	F Ratio	F Sig	N
Equation 3 (OL)	4.165	None	0.345	0.105	0.432	20.742	
Equation 6 (TH)	3.841	None	0.560	0.313	1.064	0.424	

Phase 3: Optional Goldberg-Quandt Test For *Heteroskedasticity* for Equations 3 and 6

Multiple Regression	Semester/ Exam	Measure of Variance	df_i	SSR	SSR/df	F Ratio	F_c $\alpha = 0.05$
Equation 3 (OL)	Spring'16/1	Residual	11	0.152	0.0139	= 0.0143/ 0.0139 = 1.03	$F_{7, 11} = 3.01$ Do Not Reject H_0
Equation 6 (TH)	Spring'15/1	Residual	7	0.100	0.0143		

Phase 3: Optional comparison test For predicted and observed Exam 1 scores.

Comparison Test Not Required

GQT Test: Yes/No. Results: _GQT test of heteroskedasticity – equal variances____________

Prepared By: ____________________. Approved By: __________________. Date: _______

Action Taken: ____

The following is a list of recommendations gathered by the authors, some of which match those of other researchers (Barron & Crooks, 2005; Cluskey et al., 2011; King et al., 2009; McCabe et al., 2001; Olt, 2002; Rogers, 2006):

i. Students must be apprised of the University's code of conduct regarding academic dishonesty and the detecting software (if available) that will be used.
ii. The OL exams must have a stringent warning about cheating printed on Page 1 of the exam.
iii. The penalty for cheating must be set high. Just issuing a warning or a threat of failing the exam does not hinder future cheating if faculty adopts a "look the other way" response which actually encourages more students to cheat and to do so more frequently (McCabe et al., 2001, p. 226). The student caught cheating not only needs to fail the exam but must also be required to drop the course and retake it the following semester.
iv. Avoid giving the same multiple choice or other style test questions in the following exam every semester. Students do have access to past exams. In the authors' opinion, an instructor must change at least 75% of her/his previous exam questions.
v. To the extent possible, avoid using a test bank from the publisher. These, or equivalent test banks, are available for purchase over the Internet. Preparing one's own question bank or modifying the publisher's test bank may be time-consuming, but it lessens the chance of cheating.
vi. Makeup exams for students who miss the regular exams must have different and more challenging questions than the regular exams so as to discourage future requests for makeup exams.
vii. Use the following anticheating options in different Web-based educational sites that do make it more difficult to cheat:

  - Present questions one at a time and/in a random fashion with no backtracking.
  - Scramble multiple choice answers so that every student gets a different answer sequence presented.
  - Provide just enough time that it would take a normal student to complete the full exam.
  - Provide multiple exams when it is possible without the knowledge of students. Both exams must have the same format with a slight change in wordings and parameters. Make a rough sketch of the seating arrangement.
  - Post answers to questions only after the exam due date.
  - Check exams with the same score to see if there is any distinctive similarity between the answers to questions.
  - Compare each student's exam times with the average for the class, especially for students getting a high score in spite of having a poor attendance record.

- A student finishing an exam in an abnormally short time may be a cheating suspect.
- Check the clock time at which cheating students started and finished the exam, and compare this with the time span of other students to determine if they worked in groups.

CONCLUSIONS AND LIMITATIONS

Academic departments include instructors from varied backgrounds that may or may not be familiar with empirical models that can be used to test if cheating takes place in their online (OL) or take-home (TH) exams. This article has presented a cheating detection framework (CDF) in a very simple and clearcut fashion, making it easier for all instructors across college and university campuses to plan and organize a cheating detection study. The CDF was developed to detect cheating in OL exams but it can also be used for any unproctored exam. For example, the OPM 350 courses had TH exams that were changed to OL exams. Both exams were unproctored but cheating was found to be higher in the TH exams. The reasons are under study but time appears to be an influencing factor. OL exam times can be set for a fixed duration in Blackboard. In contrast, students can take a longer time to complete TH exams, which provide increased opportunity for cheating.

Some advantages can be ascribed to the CDF. First, the framework will alleviate the necessity of doing a literature review to find the right empirical model to apply for the test. Second, it organizes the appropriate model at each phase in an ascending complexity level, giving an instructor the flexibility of choosing a suitable model(s) from Phases 1, 2, and 3. Finally, the graphical and statistical models included in the framework have been successfully applied by researchers and proven to produce results with a high level of significance.

The optional GQT failed to uncover unequal variances for OL and IC exams in Group 1, and OL and TH exams in Group 6 (refer to Table 3). Consequently, the GQT finds no cheating in both the groups of unproctored exams, while the other graphs and statistical models in Phases 1, 2, and 3 concluded that cheating has taken place in Group 1 and was undecided for Group 6 (Table 3). The GQT test of heteroskedasticity also failed to detect cheating behaviour in unproctored exams for an introductory statistics courses (Fask et al., 2015).

When the GQT was applied to the two subgroups 1 and 6 within each regression equation, it resulted in homoscedasticity (equal variance), This satisfies the Gauss-Markov Theorem which states that the ordinary least squares (OLS) will still be unbiased but will not be the best linear unbiased estimator (BLUE) of the coefficients (Murray, 2006). The unequal variance within each regression equation produces erroneous results for the test of hypothesis and regression analysis. In this study, two independent discrete data sets, the OL and IC exams, failed the test for unequal variance, which is why the OLS remains the BLUE of the coefficients.

A future study planned by the authors includes comparing the impact of cheating after implementing the interventions that are recommended in the Interventions for Mitigating Cheating section. This study would be an extension of the earlier studies on cheating in objective types of exams (Bellezza & Bellezza, 1989; Holland, 1996).

The framework experienced problems during the test for Group 6 due to very narrow differences in the mean exam scores. In such borderline cases, the CDF does provide decisive results, thereby shifting the decision making back to the instructor. Even with all of the limitations discussed earlier, the CDF is still a powerful deterrent that can mitigate the concerns that an institution's stakeholders might have about the reliability of their programs.

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