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Turnitin Systems: A Deterrent to Plagiarism in College Classrooms

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Abstract

Computer technology and the Internet now make plagiarism an easier enterprise. As a result, faculty must be more diligent in their efforts to mitigate the practice of academic integrity, and institutions of higher education must provide the leadership and support to ensure the context for it. This study explored the use of a plagiarism detection system to deter digital plagiarism. Findings suggest that when students were aware that their work would be run through a detection system, they were less inclined to plagiarize. These findings suggest that, regardless of class standing, gender, and college major, recognition by the instructor of the nature and extent of the plagiarism problem and acceptance of responsibility for deterring it are pivotal in reducing the problem. (Keywords: plagiarism, plagiarism detection, cheating, Turnitin)

By most accounts, the number of instances of academic misconduct in higher education is high and increasing. The first large-scale study on academic dishonesty was conducted in 1964. The study involved a sample of 5,000 students from 99 colleges and universities in the United States and revealed that three-fourths of the students reported engaging in some form of academic dishonesty (Bowers, 1964). More recently, the evidence suggests an increasing prevalence of academic dishonesty, particularly plagiarism (Macdonald & Carroll, 2006; Bernardi, Baca, Landers, & Witek, 2008; Roberts, 2007). Plagiarism, for the purposes of this research, is defined as the practice of taking someone else's work, idea, etc., and passing it off as one's own (Oxford English Dictionary, 2008).

The impetus for this research grew out of literature pointing to an escalating trend in digital plagiarism and the use of detection systems to mitigate it. Therefore, the primary purpose of this study was to investigate the prevalence of plagiarism (i.e., non-original work) in large introductory classes when a plagiarism detection system was and was not used. In addition, the study sought to examine the prevalence of plagiarism across various demographic characteristics, including gender, class standing, and major. The goal of the current study was to determine whether plagiarism detection systems could reduce the prevalence of plagiarism in student assignment submissions. The primary theoretical framework of this research was behavioral: to determine whether or not incentives and disincentives can be effective deterrents to plagiarism. However, this approach was not considered an "all or none" perspective and was complimented by a cognitive or values-setting strategy of educating students about what plagiarism is and the seriousness of engaging in it.

Review of Literature

Most researchers conclude that digital plagiarism—Internet or computer-driven copying without attribution—is rampant (e.g., Macdonald & Carroll, 2006; Walker, 2010) and has been for some time. Although the focus of the research reported here is post K–12, plagiarism is not confined to higher education. A large and developing database indicates plagiarism's nature, prevalence, and strategies to reduce it in the secondary education context (e.g., see Conradson & Hernández-Ramos, 2004). Across the education spectrum, studies indicate that digital plagiarizing has surpassed conventional forms of plagiarizing from classmates or printed material (Butakov & Scherbinin, 2009; Tackett, Claypool, Wolf, & Antenucci, 2010). Observers note that in the past, plagiarism required a lot of work: going to the library, searching, reading, and copying. However, a paper now can be put together by using online or digital sources in a fraction of the time (Batane, 2010; Tackett et al., 2010). In short, computer technology and the Internet now make plagiarism an easy enterprise. A major implication of this state of affairs is that faculty will need to be more diligent in their efforts to mitigate the practice, especially those who educate large numbers of students (Ledwith & Risquez, 2008).

Contributing Factors

A significant issue in digital plagiarism is students' different perceptions of what constitutes cheating. In one study, almost 25% of 698 students self-reported that they went online and cut and pasted text without proper referencing (Scanlon & Neumann, 2002). Yet Baker, Thornton, and Adams (2008) found that although 90% of the students they surveyed admitted to some kind of cheating, they did not perceive digital plagiarizing to be cheating or academic dishonesty. Other researchers report similar results (Baker, Berry, & Thornton, 2008; Dee & Jacob, 2010; Tackett et al., 2010).

Faculty's lack of commitment by faculty to counter plagiarism is another factor contributing to the practice and is particularly relevant to this research's focus. Numerous studies have indicated that where students perceive instructors to be vigilant and fair, the students were less likely to cheat (Faucher & Caves, 2009; Lemons, Martin, & Seaton, 2011; Milliron & Sandoe, 2008). Despite these findings that better monitoring could possibly reduce the propensity to cheat, authorities noted that many faculty complain that they do not have the time, resources, or administrative support to undertake such a task (Ameen, Guffey, & McMillian, 1996; Callahan, 2007; Sterngold, 2004). Given this problem, in the contemporary university of large classrooms, anonymity of behavior, and online instruction, faculty need to better understand students' decision making on the plagiarism issue.

When looking at students' integrity decisions, researchers have used several theories. Of particular interest for this study is Utility Theory, as it provides an excellent basis for understanding integrity decisions (Rettinger, 2007). Utility Theory is based on rational decision principles from the field of economics. Basically in this theory, the individuals evaluate each choice on the basis of the value (utility) of each possible outcome of that choice. In the case of academic integrity, the choice is whether to plagiarize or not. The outcomes are measured by number of points received, possible sanctions if caught, and any personal value the student places on learning. To make a decision, the student must weigh the likelihood of each possible result of each option (plagiarize or not) and balance the values of the possible results for each choice with each outcome's likelihood. In this context, given the right circumstances (i.e., low chance of being caught, mild penalties, and anonymity of behavior), plagiarizing may be the rational decision, especially if measured against the time saved (Woessner, 2004). When applying Utility Theory, one first notes the importance of consequences of behavior. Woessner (2004) stated that the only effective consequence for cheating would be one that would strongly affect the expected utility of cheating (i.e, get a zero, fail the course, be suspended). Administrators and faculty often reject these severe penalties. Thus, a more sensible alternative is to increase students' estimated (and actual) likelihood of being caught. One way to achieve this is to increase vigilance on the part of the faculty, and the other is to generate a perception among students that being caught is more likely (Rettinger, 2007).

Plagiarism Detection Technology

Plagiarism research in higher education has largely concentrated on self-reporting rather than actual plagiarism prevalence (e.g., Hawley, 1984; Rakovski & Levy, 2007; Scanlon & Neumann, 2002). Wide discrepancies between what respondents report as their own behavior and what may be true, as well as what their peers are perceived to do, casts doubt on the accuracy of self-reporting (Newstead, Franklyn-Stokes, & Armstead, 1996; Pickard, 2005). For example, Martin, Rao, and Sloan (2009) found that the instances of plagiarism were actually higher than students were willing to admit in self-report surveys. Consequently, plagiarism detection systems offer educational research a direct empirical measurement of the behavior rather than speculation based on hearsay (Scanlon, 2003).

In addition to catching plagiarism when it occurs, detection systems also can be useful in deterring plagiarism outright. Evidence suggests that students are concerned about inadvertent plagiarism (Dahl, 2007; Martin, Stubbs, & Troop, 2006), so many detection systems are now available to students directly (Badge & Scott, 2009). Many institutionally implemented systems also allow students to view their reports, discuss them with faculty, and resubmit the corrected work (Barrett & Malcolm, 2006; Ledwith & Risquez, 2008). It is noteworthy that while faculty understand the value of using this system in accordance with direct one-on-one feedback to improve student academic skills, many are not able to provide such support (Ledwith & Risquez, 2008).

Efficacy of Plagiarism Detection Technology

The development of a variety of electronic detection plagiarism systems has spawned a number of reviews of their effectiveness (e.g., Briggs, 2008; Weber-Wulff, 2007). In one of the most influential policy studies, Bull, Collins, Coughlin, Sharp, and Square (2001) tested the accuracy of four electronic plagiarism detection systems: Turnitin, EVE, Copycatch, and Wordcheck. The detection systems were rated on how effectively they discovered non-attributed text matches, although direct comparison was problematic because they operated within different parameters. Copycatch rated the highest in student-student collusion detection, but Turnitin was the only one that checked for student–student collusion, papers purchased from writing sites, and cutting and pasting from the Internet in one application (Carroll & Appleton, 2001).

Kakkonen and Mozgovoy (2010) examined a number of detection systems for student essays and concluded that systems were differentially effective, depending on the nature and form of the information source and plagiarism style. For example, Turnitin was the most advanced for detecting semi-automatic forms of plagiarism, and SafeAssignment was best for detecting Web plagiarism. They concluded that none of the systems they examined was capable of effective detection using both Internet and local sources and overcoming, at the same time, technical strategies to avoid detection. Subsequently, they point to the potential of developing and using more effective detection technologies in the future (Mozgovoy & Cosma, 2010).

Turnitin detection software is the most globally utilized plagiarism detection service available (Batane, 2010; Scherbinin, 2009). The system compares submitted papers to the ones from its database and provides a report that indicates the percentage of similarity between the two (Davis & Carroll, 2009; Scherbinin, 2009). Though not all studies support the accuracy and effectiveness of this text-matching software (e.g., Kaner & Fielder, 2008; Potthast, Stein, Barron-Cedeño, & Rosso, 2010), a large body of evidence suggests that this software can be an effective tool in detecting plagiarism (e.g., Batane, 2010; Ogilvie & Stewart, 2010; Tackett et al., 2010; Walker, 2010). However, the research to date has been unable to definitively separate the use of Turnitin as an educational tool (that is, a tool to teach students what

Table 1. Demographic Data for Class Population and Samples

	Fall 2010		Spring 2011	
	Total Class ($n = 997$)	Sample ($n = 360$)	Total Class ($n = 537$)	Sample ($n = 304$)
Freshman	496 (50%)	179 (49%)	263 (49%)	134 (44%)
Sophomore	299 (30%)	101 (28%)	66 (12%)	55 (18%)
Junior	126 (13%)	58 (16%)	108 (20%)	51 (17%)
Senior	70 (6%)	25 (7%)	100 (18%)	60 (20%)
Graduate	6 (1%)	< 1%	3 (1%)	< 1%
Male	390 (39%)	206 (57%)	202 (38%)	191 (62%)
Female	607 (61%)	164 (43%)	335 (62%)	113 (38%)

plagiarism is) versus its strictly deterrent effect of the fear of being caught. Thus, the primary objective of the current study was to determine whether or not using the Turnitin detection system solely as a detection tool serves as a deterrent.

Method

Sample

We used secondary data of Turnitin originality scores collected and available from two previous semesters of Introduction to Sociology courses taught by the same instructor at a southern university. We chose this course because it satisfies the introductory social science course general education requirement, and students from many departments throughout the university take the class, providing a divergent sample of students. During the fall 2010 semester, 997 students completed the course, and in the spring 2011 semester, 537 students completed the course. As fall 2010 consisted of nine sections and spring 2011 consisted of four sections, we used a randomized number table to select a random sample of sections. We chose four sections from the fall 2010 semester and three sections from the spring 2011 semester, rendering 360 cases in fall 2010 and 304 cases in spring 2011. Table 1 illustrates the demographic data for the students taking the course. Both semesters were similar in terms of college of major, with arts and sciences making up approximately 30% (fall: 108, spring: 91) per semester and business (fall: 29, spring: 54) making up about 18% per semester.

Procedure

The Institutional Review Board of the host university approved this study. Students were enrolled in an Introduction to Sociology undergraduate course. The syllabi of all classes provided the academic integrity policy of the university, but the instructor did not discuss this. It was expected that the students would read the syllabus and thus the policy. No changes to the institutional policy or class policy were made during the study.

In the fall 2010 semester, the instructor submitted the student papers to the detection system at the completion of the semester. Students were not aware that this was done. In the spring 2011 semester, students were required to submit work to the instructor through the Turnitin plagiarism detection system; thus, they were aware that the instructor was using the detection system.

For this study, the same chapter assignments were used for both semesters, and assignments required application of textbook material to a sociological issue. Students were given 5 days to complete each assignment and were required to use APA format and textbook referencing. Papers were required to be more than one page in length, and students submitted them electronically to the instructor via the class site on the learning management system. Turnitin was available on the e-learning system for the spring 2011 students.

Intervention: Turnitin Detection System

iParadigms' Turnitin system was introduced in 1997 and has been used in both K–12 and higher education contexts. In 2008, the system survived legal challenges by students claiming the service violated their copyright by storing their work without permission and using it as part of a for-profit business (iParadigms, 2011). iParadigms' massive databases include an archive of all the papers previously submitted to Turnitin (more than 130 million) plus content from millions of Web sites (more than 13 billion pages), academic publications, online encyclopedias, news agencies, and other sources likely to be used for plagiarism (iParadigms, 2011). As is the case with other detection systems, Turnitin compares the writer's sentences with its databases to provide a non-originality score—a percentage linked to an identified source—so the investigator can compare the original work with the reproduced material (Walker, 2010). Unlike many other detection systems, Turnitin compares papers not only for student–student collusion but also to many outside sources.

Students were required to submit assignments to the instructor through Turnitin, which was directly linked to the class site on the learning management system. Students could only submit the assignment once and did not have access to their originality scores.

Measure

The researcher relied on Turnitin to analyze the submitted assignments. For each paper, a similarity, or overlap, score identified the percentage of submitted text that matched Turnitin's continually updated database. Turnitin uses percentage groupings of 0–24%, 25–49%, 50–74%, and 75–100% for quick comparison, with higher overlap scores indicating greater plagiarism. However, for the purpose of this study, exact percentages were used to provide a

Table 2. Descriptive Statistics for Prevalence of Plagiarism (Percentage Overlap Averaged Across Three Assignments) When Students Are Unaware and Aware of Plagiarism Detection Systems

	Students Unaware of Detection Systems				Students Aware of Detection Systems			
Plagiarism Source	Min	Max	*M*	*SD*	Min	Max	*M*	*SD*
Internet		48.67	5.43	7.44	0.00	32.67	4.36	5.03
Publication	0.00	6. 67	0.33	1.10	0.00	18.00	0.54	1.56
Student	0.00	76.00	16.33	16.92	0.00	48.33	9.34	8.80
Overall	0.00	76.00	16.55	16.97	0.00	48.67	9.76	8.93

more precise measure of plagiarism. We calculated average percentages of overlapped material across three assignments for the semester and compared them across groups.

Analyses

We performed analyses using SPSS for Windows Version 19. We used means and standard deviations to describe the data. We conducted analysis of variance to determine whether there were significant differences in average percentage of plagiarized material across gender, class standing, and college major. We ran independent samples t-tests to determine whether there were significant differences in plagiarism between the two semesters—that is, whether plagiarism was more prevalent in classes where students were unaware of the detection system being used than in classes where it was known to be used. We conducted hierarchical multiple regression using simultaneous entry at each block to examine the impact of the use of Turnitin software on percentage of plagiarism in students' work, controlling for gender and class standing. We entered gender and class standing on the first step of the regression analysis and added the use of Turnitin software to the second step. We completed this procedure for each criterion variable (i.e., type of plagiarism). We conducted all analyses at the $\alpha = .05$ level of significance. Assumptions of tests were examined and were not violated, except where noted.

Results

Table 2 displays the descriptive statistics of the prevalence of plagiarism when students were aware and unaware of Turnitin being used to evaluate assignments for plagiarism. Results indicated that in classes where students were unaware of the plagiarism detection system being used, student assignments ranged from 0% to 76% overall overlap, with a mean of 16.55% (SD = 16.97). Results indicated that the largest source used to plagiarize was from other students; student overlap ranged from 0% to 76%, with a mean of 16.33% (SD = 16.92). Internet as a plagiarism source ranged from 0% to 48.67% overlap, with a mean of 5.43% (SD = 7.44). Publications as a plagiarism source ranged from 0% to 6.67% overlap, with a mean of 0.33% (SD = 1.10).

Table 3. Plagiarism (Percentage Overlap Averaged Across Three Assignments) as a Function of Gender: Naïve and Informed Subsamples

	Naïve Subsample				Informed Subsample			
Plagiarism Source	*M*	*SD*	*F*	*p*	*M*	*SD*	*F*	*p*
Overall			2.90	.09			8.55	.004*
Male	17.86	16.89			10.90	8.98		
Female	14.79	16.97			7.84	8.55		
Internet			3.45	.06			4.49	.04*
Male	6.06	8.22			4.83	5.09		
Female	4.59	6.18			3.57	4.84		
Publication			1.09	.30			0.39	.53
Male	0.38	1.12			0.58	1.76		
Female	0.26	1.06			0.47	1.13		
Student			2.39	.12			9.60	.002*
Male	17.52	16.83			10.52	8.87		
Female	14.74	16.97			7.33	8.34		

* *Significant* p *value* (p < .05)

Results indicated that in classes where students were aware of a plagiarism detection system being used, student assignments ranged from 0% to 48.67% overall overlap, with a mean of 9.76% ($SD = 8.93$). Results indicated that the largest source used to plagiarize was from other students, with an average plagiarism rate of 9.34% ($SD = 8.8$) within a range from 0% to 48.33%. Internet as a plagiarism source ranged from 0% to 32.67% overlap, with a mean of 4.36% ($SD = 5.03$). Publications as a plagiarism source ranged from 0% to 18% overlap, with a mean of 0.54% ($SD = 1.56$).

Demographic Comparisons: Total Sample

Table 3 displays the average plagiarism rates across the three assignments as a function of gender for the naïve subsample, informed subsample, and the total sample. We conducted a series of analyses of variance to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across genders for the naïve subsample. Results indicated no significant differences across genders in percentage of overall overlap, $F(1, 358) = 2.90, p = .09$; in percentage of Internet overlap, $F(1,358) = 3.45, p = .06$; in percentage of publication overlap, $F(1, 358) = 1.09, p = .30$*; or in percentage of student overlap, $F(1, 358) = 2.39, p = .12$. (Note: For all analyses marked with *, Levene's test for homogeneity of variance was significant, indicating that this assumption was violated. As such, results should be interpreted with caution.)

We conducted a series of analyses of variance to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across genders for the informed subsample. Results indicated a significant difference between genders in the percentage of overall overlap, $F(1, 309) = 8.55$, $p = .004$. Males ($M = 10.90$, $SD = 8.98$) had higher percentages of overall overlap than did females ($M = 7.84$, $SD = 8.55$). Results indicated a significant difference between genders in the percentage of Internet overlap, $F(1, 302) = 4.49$, $p = .04$. Males ($M = 4.83$, $SD = 5.09$) had higher percentages of Internet overlap than did females ($M = 3.57$, $SD = 4.84$). Results indicated a significant difference between genders in the percentage of student overlap, $F(1, 302) = 9.60$, $p = .002$. Males ($M = 10.52$, $SD = 8.87$) had higher percentages of student overlap than did females ($M = 7.33$, $SD = 8.34$). Results indicated no significant difference between genders in the percentage of student overlap, $F(1, 302) = .39$, $p = .53$.

We conducted a series of analyses of variance to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across gender for the total sample. Results indicated significant differences between genders in percentage of overall overlap, $F(1, 662) = 5.59$, $p = .02$. Males ($M = 14.51$, $SD = 14.09$) had higher percentages of overall overlap than did females ($M = 11.85$, $SD = 14.43$). Results indicated significant differences between genders in percentage of Internet overlap, $F(1, 662) = 6.57$, $p = .01$. Males ($M = 5.46$, $SD = 6.91$) had higher percentages of Internet overlap than did females ($M = 4.16$, $SD = 5.67$). Results indicated no significant differences between genders in percentage of publication overlap, $F(1, 662) = 1.55$, $p = .21$*. Results indicated significant differences between genders in percentage of student overlap, $F(1, 662) = 5.16$, $p = .02$. Males ($M = 14.15$, $SD = 14.02$) had higher percentages of student overlap than did females ($M = 11.60$, $SD = 14.44$).

Table 4 (p. 238) displays the average plagiarism rates across the three assignments as a function of class standing for the naïve subsample, informed subsample, and total sample. We conducted a series of analyses of variance with Tukey's post-hoc analysis to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across class standings for the naïve subsample. Results indicated no significant differences across class standings in percentage of overall overlap, $F(4, 355) = 0.64$, $p = .64$; in percentage of Internet overlap, $F(4,355) = 1.08$, $p = .37$; in percentage of publication overlap, $F(4, 355) = 1.67$, $p = .16$*; or in percentage of student overlap, $F(4, 355) = 0.67$, $p = .61$.

We conducted a series of analyses of variance with Tukey's post-hoc analysis to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across class standings for the informed subsample. Results indicated no significant differences across class standings in the percentage of overall overlap, $F(4, 299) = 0.59$, $p = .67$; in the percentage of Internet overlap, $F(4,299) = 0.54$, $p = .71$*; in the percentage of publication overlap, $F(4, 299) = 0.62$, $p = .65$; or in the percentage of student overlap, $F(4, 299) = 0.62$, $p = .65$.

We conducted a series of analyses of variance with Tukey's post-hoc analysis to determine whether there were significant differences in percentage

Table 4. Plagiarism (Percentage Overlap Averaged across Three Assignments) as a Function of Class

	Naïve Subsample				Informed Subsample				Total Sample			
Plagiarism Source	*M*	*SD*	*F*	*p*	*M*	*SD*	*F*	*p*	*M*	*SD*	*F*	*p*
Overall			0.64	.64			0.59	.67			1.15	.33
Freshman	15.37	17.19			9.92	8.18			13.01	14.25		
Sophomore	17.85	18.13			8.48	9.10			14.56	16.17		
Junior	18.53	14.52			11.03	9.50			14.92	12.87		
Senior	15.67	15.96			9.40	9.89			11.22	12.21		
Graduate	11.33	19.63			11.33	11.31			11.33	14.99		
Internet			1.08	.37			0.54	.71			1.40	.23
Freshman	4.81	7.58			4.32	4.04			5.49	6.29		
Sophomore	5.56	7.52			4.37	5.59			5.14	6.91		
Junior	6.98	7.00			5.10	6.89			6.08	6.98		
Senior	6.04	7.20			3.88	4.69			4.51	5.58		
Graduate	2.67	4.62			2.00	0.47			2.40	3.29		
Publication			1.67	.16			0.62	.65			1.15	.33
Freshman	0.29	0.97			0.55	1.84			0.41	1.42		
Sophomore	0.20	0.90			0.57	1.24			0.33	1.05		
Junior	0.63	1.51			0.69	1.68			0.66	1.59		
Senior	0.47	1.47			0.32	0.86			0.36	1.07		
Graduate	0.00	0.00			1.50	2.12			0.60	1.34		
Student			0.67	.61			0.62	.65			1.08	.37
Freshman	15.10	17.08			9.57	8.08			12.70	14.16		
Sophomore	17.76	18.12			7.88	8.79			14.29	16.17		
Junior	18.26	14.54			10.40	9.43			14 47	12.91		
Senior	15.48	16.02			9.14	9.78			10 98	12.18		
Graduate	11.33	19.63			11.33	11.31			11 33	14.99		

* *Significant* p *value* ($p < .05$)

of overlap (overall, Internet, publication, and student) across class standings for the total sample. Results indicated no significant differences across class standings in percentage of overall overlap, $F(4, 659) = 1.15, p = .33$. Results indicated no significant differences across class standings in percentage of Internet overlap, $F(4, 659) = 1.40, p = .23$*. Results indicated no significant differences across class standings in percentage of publication overlap, $F(4, 659) = 1.15, p = .33$*. Results indicated no significant differences across class standings in percentage of student overlap, $F(4, 659) = 1.08, p = .37$.

Table 5 displays the average plagiarism rates across the three assignments as a function of college major for the naïve subsample, informed subsample, and total sample. We conducted a series of analyses of variance with Tukey's post-hoc analysis to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across college majors for the naïve subsample. Results indicated no significant differences across college

Table 5. Plagiarism (Percentage Overlap Averaged across Three Assignments) as a Function of College Major

	Naïve Subsample				Informed Subsample				Total Sample			
Plagiarism Source	*M*	*SD*	*F*	*p*	*M*	*SD*	*F*	*p*	*M*	*SD*	*F*	*p*
Overall			0.68	.69			0.92	.49			0.61	.75
A & S	15.11	16.16			8.78	8.76			12.46	13.89		
Business	16.94	17.34			8.84	8.22			13.76	14.95		
Comp Science	18.25	14.78			9.38	8.41			13.62	12.62		
Education	18.50	18.79			11.42	8.12			15.37	15.34		
Engineering	11.84	13.17			10.16	7.66			11.13	11.08		
HES	19.52	20.38			9.18	6.93			14.35	16.00		
Social Work	17.40	13.38			14.94	15.93			16.48	13.91		
Nursing	16.34	18.24			11.49	11.43			13.45	14.64		
Internet			0.97	.45			0.60	.75			0.68	.69
A & S	5.16	7.45			4.16	5.13			4.74	6.58		
Business	5.75	6.90			3.40	4.23			4.83	6.08		
Comp Science	7.79	10.23			4.76	4.74			6.21	7.95		
Education	5.98	7.21			4.84	4.95			5.48	6.29		
Engineering	3.68	6.52			5.47	5.22			4.44	6.00		
HES	3.99	5.41			4.71	4.57			4.35	4.99		
Social Work	5.70	5.29			6.28	6.87			5.92	5.71		
Nursing	5.71	8.69			4.06	5.97			4.72	7.18		
Publication			2.71	.01*			0.94	.47			2.03	.05*
A & S	0.26	1.03			0.28	0.81			0.27	0.94		
Business	0.26	0.99			0.61	1.18			0.40	1.08		
Comp Science	0.17	0.71			0.32	0.88			0.24	0.80		
Education	0.12	0.58			0.99	3.46			0.50	2.36		
Engineering	0.09	0.42			0.57	0.93			0.29	0.72		
HES	0.67	1.24			0.67	1.45			0.67	1.34		
Social Work	1.40	2.16			0.61	1.50			1.10	1.92		
Nursing	0.53	1.66			0.75	1.83			0.66	1.76		
Student			0.64	.73			1.09	.37			0.54	.80
A & S	15.00	16.06			8.43	8.67			12.25	13.83		
Business	16.65	17.31			8.11	8.03			13.29	14.95		
Comp Science	18.05	14.76			9.01	8.10			13.34	12.54		
Education	17.66	18.79			10.94	7.95			14.68	15.26		
Engineering	11.68	13.08			9.55	7.23			10.78	10.91		
HES	19.42	20.38			8.64	6.67			14.03	16.01		
Social Work	17.40	13.38			14.61	16.11			16.35	13.99		
Nursing	16.28	18.26			11.38	11.37			13.36	14.63		

* *Significant* p *value* ($p < .05$)

majors in percentage of overall overlap, $F(7, 352) = 0.68$, $p = .69$. Results indicated no significant differences across college majors in percentage of Internet overlap, $F(7, 352) = 0.97$, $p = .45$. Results indicated no significant differences across college majors in percentage of student overlap, $F(7,352) = 0.64$, $p = .73$. Results indicated a significant difference across college majors in the percentage of publication overlap, $F(7, 352) = 2.71$, $p = .01^*$. Social work majors ($M = 1.40$, $SD = 2.16$) had higher percentages of publication overlap than did arts and sciences majors ($M = .29$, $SD = 1.03$), business majors ($M = .26$, $SD = .99$), computer science majors ($M = .17$, $SD = .71$), education majors ($M = .12$, $SD = .58$), engineering majors ($M = .09$, $SD = .42$), or nursing majors ($M = .53$, $SD = 1.66$). Human environmental science majors ($M = .67$, $SD = 1.24$) were not different from any other group.

We conducted a series of analyses of variance with Tukey's post-hoc analysis to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across college majors for the informed subsample. Results indicated no significant differences across college majors in the percentage of overall overlap, $F(7, 296) = .92$, $p = .49^*$; in the percentage of Internet overlap, $F(7, 296) = .75$, $p = .60$; in the percentage of publication overlap, $F(7, 296) = .94$, $p = .47^*$; or in the percentage of student overlap, $F(7, 296) = 1.09$, $p = .37^*$.

We conducted a series of analyses of variance with Tukey's post-hoc analysis to determine whether there were significant differences in percentage of overlap (overall, Internet, publication, and student) across college majors for the total sample. Results indicated significant differences across college majors in percentage of publication overlap, $F(7, 656) = 2.03$, $p = .05$. Social work ($M = 1.10$, $SD = 1.92$) had higher percentages of publication overlap than did arts and sciences ($M = .27$, $SD = .94$), business ($M = .40$, $SD = 1.08$), computer science ($M = .24$, $SD = .80$), education ($M = .50$, $SD = 2.36$), engineering ($M = .29$, $SD = .72$), human environmental sciences ($M = .67$, $SD = 1.34$), and nursing ($M = .65$, $SD = 1.76$). Results indicated no significant differences across college majors in percentage of overall overlap, $F(7, 656) = 0.61$, $p = .75$; in percentage of Internet overlap, $F(7, 656) = 0.68$, $p = .69$; or in percentage of student overlap, $F(7, 656) = 0.54$, $p = .80$.

The Impact of Awareness: Naïve vs. Informed Students

We ran independent samples t-tests to determine whether knowledge of a plagiarism detection system had an impact on student plagiarism—that is, whether there were differences in the percentage of plagiarism in student assignments depending on whether or not students were aware that plagiarism detection systems were being used. For all analyses, Levene's test for homogeneity of variance was significant, indicating that this assumption was violated. As such, we interpreted results of the *t*-tests without assumption of equal variances. Results indicated significant differences in percentage of overall overlap across semesters, $t(561.63) = 6.58$, $p < .001$. Specifically, stu-

Table 6. Hierarchical Multiple Regression Analysis Results for the Effectiveness of Turnitin Software on Internet Plagiarism, Controlling for Gender and Class Standing

Model/Predictor	B (SE)	β	Part r	t
Model 1: $R^2 = .01$				
Gender	-1.32 (0.51)	-.10	-.10	-2.59*
Class standing	0.17 (0.23)	.03	.03	0.75
Model 2: $R^2 = .02$				
Gender	-1.40 (0.51)	-.11	-.11	-2.75*
Class standing	0.25 (0.23)	.04	.04	1.10
Turnitin software	-1.23 (0.51)	-.10	-.10	-2.42*

** Significant p value (p < .05)*

dents who were aware that a plagiarism detection system was being used had lower percentages of plagiarism ($M = 9.76$, $SD = 8.93$) than did students who were unaware that these methods were being used ($M = 16.55$, $SD = 16.97$). Results indicated significant differences in percentage of Internet overlap across semesters, $t(633.05) = 2.19$, $p = .03$. Students who were aware that a plagiarism detection system was being used had lower percentages of Internet plagiarism ($M = 4.36$, $SD = 5.03$) than did students who were unaware that these methods were being used ($M = 5.43$, $SD = 7.44$). Results indicated significant differences in percentage of student overlap across semesters, $t(557.93) = 6.82$, $p < .001$. Students who were aware that a plagiarism detection system was being used had lower percentages of student plagiarism ($M = 9.39$, $SD = 8.80$) than did students who were unaware that these methods were being used ($M = 16.33$, $SD = 16.92$). Results indicated no significant differences in percentage of publication overlap across semesters, $t(531.71) = -2.00$, $p = .05$. Students who were aware that a plagiarism detection system was being used had similar percentages of publication plagiarism ($M = 0.54$, $SD = 1.56$) than did students who were unaware that these methods were being used ($M = 0.32$, $SD = 1.10$).

Controlling for Gender and Class Standing

Hierarchical regression analysis revealed that gender and class standing significantly predicted Internet plagiarism, $R^2 = .01$, $F(2, 661) = 3.57$, $p = .03$. The addition of Turnitin software in the second step added significantly to the prediction of Internet plagiarism, $\Delta R^2 = .01$, $\Delta F(1, 660) = 5.87$, $p = .02$. Examination of standardized beta coefficients in the final model revealed that gender ($\beta = -.11$) and Turnitin software ($\beta = -.10$) contributed significantly to the prediction of Internet plagiarism, such that males and students who were unaware that Turnitin software would be used were more likely to plagiarize (see Table 6).

A second hierarchical regression analysis revealed that gender and class standing did not significantly predict publication plagiarism, $R^2 = .003$, $F(2, 661) = 1.01$, $p = .37$. The addition of Turnitin software in the second step did not improve upon our prediction of publication plagiarism, $\Delta R^2 = .01$, $\Delta F(1, 660)$

Table 7. Hierarchical Multiple Regression Analysis Results for the Effectiveness of Turnitin Software on Publication Plagiarism, Controlling for Gender and Class Standing

Model/Predictor	B (SE)	β	Part r	t
Model 1: $R^2 = .003$				
Gender	-0.13 (0.11)	-.05	-.05	-1.27
Class standing	0.03 (0.05)	.03	.03	0.68
Model 2: $R^2 = .01$				
Gender	-0.12 (0.11)	-.05	-.05	-1.15
Class standing	0.02 (0.05)	.02	.02	0.39
Turnitin software	0.20 (0.11)	.08	.08	1.91

* *Significant* p *value* ($p < .05$)

Table 8. Hierarchical Multiple Regression Analysis Results for the Effectiveness of Turnitin Software on Student Plagiarism, Controlling for Gender and Class Standing

Model/Predictor	B (SE)	B	Part r	t
Model 1: $R^2 = .01$				
Gender	-2.54 (1.13)	-.09	-.09	-2.26*
Class standing	-0.10 (0.50)	-.01	-.01	-0.20
Model 2: $R^2 = .06$				
Gender	-3.01 (1.09)	-.10	-.09	-2.75*
Class standing	0.38 (0.49)	.03	-.01	0.78
Turnitin software	-7.28 (1.08)	-.26	-.25	-6.72*

* *Significant* p *value* ($p < .05$)

$= 3.63$, $p = .06$. Examination of standardized beta coefficients in the final model revealed that none significantly predicted publication plagiarism (see Table 7).

A third hierarchical regression analysis revealed that gender and class standing did not significantly predict student plagiarism, $R^2 = .01$, $F(2, 661) = 2.59$, $p = .08$. However, the addition of Turnitin software in the second step added significantly to the prediction of student plagiarism, $\Delta R2 = .06$, $\Delta F(1, 660) = 45.11$, $p < .001$. Examination of standardized beta coefficients in the final model revealed that gender ($\beta = -.10$) and Turnitin software ($\beta = -.26$) contributed to the prediction of student plagiarism, such that males and students who were unaware that Turnitin software would be used were more likely to plagiarize (see Table 8).

Finally, a fourth hierarchical regression analysis revealed that gender and class standing did not predict overall plagiarism, $R^2 = .01$, $F(2, 661) = 2.81$, $p = .06$. However, the addition of Turnitin software in the second step added significantly to the prediction of overall plagiarism, $\Delta R^2 = .01$, $\Delta F(1, 660) = 42.17$, $p < .001$. Examination of standardized beta coefficients in the final model revealed that gender ($\beta = -.11$) and Turnitin software ($\beta = -.25$) contributed significantly to the prediction of overall plagiarism, such that males and students who were unaware that Turnitin software would be used were more likely to plagiarize (see Table 9).

Table 9. Hierarchical Multiple Regression Analysis Results for the Effectiveness of Turnitin Software on Overall Plagiarism, Controlling for Gender and Class Standing

Model / Predictor	B (SE)	β	Part r	t
Model 1: $R^2 = .01$				
Gender	-2.66 (1.13)	-.09	-.09	-2.35*
Class standing	-0.10 (0.50)	-.01	-.01	-0.20
Model 2: $R^2 = .06$				
Gender	-3.11 (1.10)	-.11	-.09	-2.83*
Class standing	0.37 (0.50)	.03	-.01	0.75
Turnitin software	-7.08 (1.09)	-.25	-.24	-6.49*

* *Significant* p *value* ($p < .05$)

Notes on Gender and Academic Major

For the total sample, males had higher plagiarism rates than females. Interestingly, males weren't higher than females for the naïve sample but were for the informed sample. This suggests that the detection strategy was more of a deterrent for females. It lowered their rates enough that it caused them to be different from males.

It has been reported consistently that business and engineering majors have higher incidences of cheating than arts and sciences (Bowers, 1964; Newstead et al., 1996, Martin, Rao, & Sloan, 2009). However, in this study, there were no differences in plagiarism rates across college majors, with the exception of publication plagiarism, though this was true only for the naïve subsample.

Discussion

A number of implications can be inferred from this research. For three of the four hierarchal regression analyses, Turnitin software significantly predicted plagiarism, even after controlling for demographics, with males and those unaware of its use being more apt to plagiarize. The fact that there were lower rates of plagiarism when students knew they were being monitored suggests the detection system was an effective prevention strategy.

Ultimately, prevention is about changing behavior, and this can be approached from both a cognitive and a social learning framework. Cognitive approaches focus on variables that promote awareness of basic values that guide our conduct, educate about what we are doing and its implications, and imply what we should shun and what we should embrace. In the case of plagiarism, the use of Turnitin software as an educational tool can educate students about what plagiarism is and about the ethics of non-attribution of others' work, whether in terms of false claims to originality or fairness to others who have struggled to be original in their ideas. The social learning approach, in contrast, shapes behavior through the use of rewards and punishments. The assumption is not only that incentives and disincentives guide our conduct, but also that our attitudes, beliefs, and values will become consistent with how we are compelled to act. In the case of plagiarism and the use of Turnitin, this translates into acknowledging and praising original work and appropriate citation for the work of others (i.e., reward) and the repercussions of being caught for lack of originality and appropriate attribution (i.e., punishment).

These are not, of course, mutually exclusive approaches, and a combination of both approaches can be more effective than a single one. For the purposes of this research, however, the focus was on the behavioral. The appeal was in the simplicity of the behavior modification technique of essentially implying: Your work will be checked for originality. If it is determined that your work is not original and/or does not carry appropriate credit for others' work, then you will be penalized. This approach is particularly inviting in the context of large classes and the relatively anonymous settings they represent. However, telling students that plagiarism will be monitored is also a cognitive and values-setting approach. Thus, the combination of strategies appears to be effective for plagiarism mediation and have implications for practice for both the instructor and the institution.

Implications for Practice

The implications of these findings and conclusions are significant from the instructor's perspective, due to both the simplicity and ease of implementation the strategies entail. Without a large investment of time and energy, the teacher has effective tools to reduce this type of behavior: (a) Make the statement of value (i.e., plagiarism is bad and, therefore, will not be tolerated) and (b) follow through on plagiarism detection and its consequences.

From the institutional perspective, it is critical that colleges and universities create a supportive context for defining plagiarism and emphasizing the seriousness of the practice as an attack on both academic and personal integrity. In recent years, higher education has sometimes been reluctant to embrace this precept in deference to "pleasing the student client" against the backdrop of fierce student recruitment. Yet primary responsibilities of the institution are to bring plagiarism issues to the fore, to explicitly and strongly assert that the practice will not be tolerated, and to communicate that faculty have primary responsibility for reinforcing this message through both instruction and detection. A corollary to institutional responsibility is that instructors cannot be "left hanging out there" when they discover such student misconduct. Administrative officials must be willing and able to back up anti-plagiarism rhetoric with punitive measures when misconduct is discovered. The adoption of Turnitin or similar plagiarism detection devices as a part of institutional policy concretizes its commitment to academic integrity.

Limitations and Directions for Future Research

A number of limitations attend this study due to the practical constraints of its timing and setting. Comparing two classes across consecutive years introduced obvious limitations posed by assessing different students at different time periods. This leaves open the possibility of extraneous and unknown variables affecting the responses. The use of Turnitin detection software has the inherent limitation of yielding an "originality score" rather than a "copying without attribution" score. In addition, the instructor did not designate a specific punishment for plagiarism, which could have altered the results.

Future research should vary types and degrees of punishment to assess their effectiveness as deterrents in these large classes. Another variable is the larger context: comparing student responses to these strategies in large research-oriented institutions of higher education that do not emphasize academic integrity with those that do. Other considerations for future research would be comparing results between first- or second-year students with juniors and seniors, using different types of schools and students, and employing experimental designs to discern more critical cause and effect relationships.

Conclusions

These findings suggest that, regardless of class demographics, recognition by the instructor of the nature and extent of the plagiarism problem and acceptance of responsibility for deterring it are pivotal in reducing it. Previous research supports the conclusion that faculty bear the largest burden in mitigating plagiarism (Howard & Davies, 2009; Staats, Hupp, Wallace, & Gresley, 2009; Tackett et al., 2010). However, empirical data addressing ways for faculty of large courses to do so is lacking. As the trends toward increased use of computer technologies and expanding commercialization of higher education continue, faculty will continue to play the most important role in preventing plagiarism in higher education.

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