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Understanding anti-plagiarism software adoption: An extended protection motivation theory perspective

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ABSTRACT

This study investigates factors affecting the adoption of anti-plagiarism software. Using protection motivation theory as a basis, this research examines the influence of threat and coping appraisals, along with social influences, moral obligation, and actual control variables, on the adoption of anti-plagiarism software. A field survey of 218 faculty members working at U.S. public universities reveals that threat appraisals have a stronger influence on the adoption of anti-plagiarism software than do coping appraisals. The faculty members' moral obligation, academic rank, class size, percentage of creative assignments, and gender significantly affect software adoption, whereas social influence does not. Key implications for theory and practice are discussed.

1. Introduction

Despite continuing efforts to educate people that Internet plagiarism is improper behavior, the misuse of the Internet as a tool for research and writing appears to be growing at an overwhelming rate (e.g., [33]). One survey reports that almost 40% of college students admitted to engaging in Internet plagiarism in 2005, up 30% since 1999. The Educational Testing Service also reports that a single "paper mill" Web site averages 80,000 hits per day [8]. This problem likely will become even more rampant as a new generation of students, who largely regard information in cyberspace as public goods and are accustomed to downloading free music, enter college in the near future [34,46].

To cope with the epidemic of Internet plagiarism, many colleges and universities add to their formal honor codes, promote greater awareness programs, enact strong enforcement policies, and install anti-plagiarism software. Of these countermeasures, systematic detection using anti-plagiarism software provides a pertinent and effective method [33]. However, contrary to what might be expected, relatively few faculty members adopt anti-plagiarism software [21]. This study seeks to explain the large gap between faculty members' concern about the use of Internet plagiarism and their minimal adoption of preventative software. Some speculation suggests they might be reluctant to adopt anti-plagiarism software, but rigorous research has yet to identify the facilitators and inhibitors of faculty members' decisions to adopt. Previous studies mainly focus on students' motivation to commit Internet plagiarism, not on faculty's role in fighting and educating students about the topic [7]. In addition, previous researchers (e.g., [37]) treat protective systems (e.g., anti-virus software, wireless security) as similar to productivity-enhancing technologies (e.g., spreadsheets, e-mail) and use generic IT adoption theories to address their adoption.

Adopting instead the stance that Internet plagiarism is a major threat to academic integrity, this study applies the protection motivation theory (PMT) [54] from health psychology and extends it to investigate factors that may affect the decision to adopt anti-plagiarism software. On the basis of a theoretical postulation of PMT, this study posits that faculty members will be more inclined to adopt anti-plagiarism software when they (1) perceive Internet plagiarism as a serious threat to upholding the standards of academic integrity, (2) are convinced that the software is an effective means of detecting and deterring the use of Internet plagiarism, and (3) believe they possess the capability to use the software.

This study also attempts to extend the original PMT in several ways. First, it examines the nomological network (i.e. the inter-relationships among and between research variables) that has been ignored in previous PMT studies and includes actual control variables that may significantly affect the adoption of anti-plagiarism software. This study examines the direct relationship between coping appraisals and the actual adoption of the software, as predicted in studies that rely on other theories, such as the theory of planned behavior [1] and the technology acceptance model [66], but not in previous PMT studies. Second, this study explores the effect of behavioral control variables, including academic rank, class size, percentage of essay-style assignments, gender, number of teaching assistants, years of employment, and teaching load, on the software adoption. Third, it

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examines the effect of moral obligation [37] and social influence [69] on faculty acceptance of anti-plagiarism software.

2. Research background

2.1. Internet plagiarism

Plagiarism, defined as “the literary theft, stealing (by copying) the words or ideas of someone else and passing them off as one's own without crediting the source” [48, p.472], is not a new phenomenon in academia. For decades, studies have reported increasing trends of student plagiarism [11,35], though the issue prompted renewed attention as the Internet, an efficient and effective tool for research and writing, grew in popularity among students, which intensified the problem [24]. The temptation to visit online sites and cut and paste from them, without proper citations, or to purchase prewritten papers from paper mills is growing, driven by (1) the ease of accessing the vast resource base of the Internet to plagiarize; (2) the widespread belief that resources on the Internet are public goods; (3) the perception of low chances of being detected and penalized, often because of a lack of educator interest; (4) the benefits of plagiarizing, particularly for students who have overtaxed, high-pressure lives; and (5) the popularity of large classes and online education, which eliminate most face-to-face contact between students and faculty [30]. Studies further report that though 89% of students recognize Internet plagiarism as wrong, almost one-quarter of them admit to committing Internet plagiarism [60]. In addition, 52% of high school juniors admitted to engaging in Internet plagiarism, which implies the problem may become more extensive when students enter college. To counteract this undesirable phenomenon, educators and researchers have devised proactive solutions, including the use of honor codes, institutional sanctions, instructions, expectation management, and anti-plagiarism software [22,60].

2.2. Anti-plagiarism software

One proactive countermeasure to cope with Internet plagiarism is anti-plagiarism software, which can help faculty detect, deter, and educate students about such plagiarism [33,60]. The software quickly detects plagiarism by trawling the Web and its own database, then matching text within students' assignments to text stored in the database, including Web documents; online publications of books, magazines, academic journals; and student papers that other faculty previously have submitted to check for plagiarism [22]. Detecting plagiarism using these automated tools is necessary, because instructors cannot keep current with every new source of information in specific detail [51]. In addition, the software can help deter students' plagiarism, because faculty can warn students of the effectiveness of the anti-plagiarism software [6]. Furthermore, it highlights plagiarized words, sentences, or sections, so the software provides an educational tool to instruct students about their incorrect usage of plagiarized words, phrases, and sections and help them learn to cite their sources properly [4,39].

The effectiveness of anti-plagiarism software has received wide support [32,60]. Jacoy and DiBiase [33] indicate that in their study, anti-plagiarism software detected a 13% plagiarism rate for assignments in an online geography course, whereas manual methods only detected a 3% rate for the same assignments. Weinstein and Dobkin [67] find a similarly significant effect: 17.5% of students who received warnings that their papers would be checked using the software engaged in plagiarism, whereas 28% of those who received no such warning did so. The various types of anti-plagiarism software, including Turnitin.com, Glatt Plagiarism Services, WCopyFind, IntegriGuard, WordCheck, and EVE2, function mainly in academia and publishing industries as efficient means to combat Internet plagiarism.

2.3. Protection motivation theory

Protection motivation theory [53,54] offers a viable theoretical framework in health and social psychology that provides an important socio-cognitive account of diverse protective behavior. As an expectancy-value theory, PMT postulates that protection motivation arises from cognitive appraisals of a threatening event as serious and likely to occur, together with the belief that a recommended coping response can prevent the event. The threat appraisal thus depends on perceptions of the severity of the expected threat and potential vulnerability to it. The likelihood of an adaptive response increases when people's perceptions of severity and vulnerability are high. Coping appraisal relates to an evaluation of one's ability to cope with and avoid the threatening behavior, that is, the person's individual assessment of the effectiveness of the proposed adaptive behavior to avert the threat (i.e., response efficacy) and his or her perceived ability to conduct that advocated behavior (i.e., self-efficacy). The likelihood of enacting an adaptive behavior increases with higher predicted levels of these efficacy variables. Moreover, the likelihood of enacting an adaptive behavior decreases when high response costs associated with performing the adaptive behavior appear likely. Examples of such perceived costs include inconvenience, expensiveness, unpleasantness, difficulty, complexity, side effects, disruption of daily life, and the ability to overcome habit strength [18]. In summary, both threat and coping appraisal variables affect a person's protective motivation, resulting in applicable adaptive responses [19]. Previous meta-analyses confirm that all threat- and coping-appraisal components of the PMT significantly contribute to the prediction and understanding of protective behaviors [18].

The PMT also has received validation for a diverse array of behaviors, including various health threats [43], preventive behaviors [56], safer-sex behaviors [62], environmental hazards [64], and adherence to medical treatment regimens [42]. Recent applications extend to the IS field, addressing especially the adoption of systems such as home wireless security [69], anti-malware software [38] and healthcare technology [9].

3. Research hypotheses

This study adopts the protection motivation theory and develops a theoretical model to address the adoption of anti-plagiarism software by faculty members (see Fig. 1). The major assumptions of the theoretical model therefore indicate that (1) the intention to adopt anti-plagiarism software is a positive linear function of four factors: (a) severity of the threat, (b) vulnerability to the threat, (c) response efficacy, and (d) self-efficacy; and (2) intention is a negative linear function of the response cost.

This study extends the theoretical boundary of the PMT by investigating the influences of social influence and moral obligation on adoption intention, as well as examining the relationship among coping appraisal variables, actual control variables, and actual software adoption.

3.1. Protection motivation variables

3.1.1. Severity of the threat

Severity refers to “the degree of physical harm, psychological harm, social threats, economic harm, dangers to others rather than oneself, and even threats to other species” ([55], p. 115). The more seriously a person perceives the magnitude of the consequences resulting from continuing maladaptive actions, the more he or she should adopt recommended adaptive actions. Previous studies find that the severity of the threat exerts a significant effect on intentions to stop smoking [50,53], conserve energy [26], and adopt security countermeasures [71] and behaviors [47].

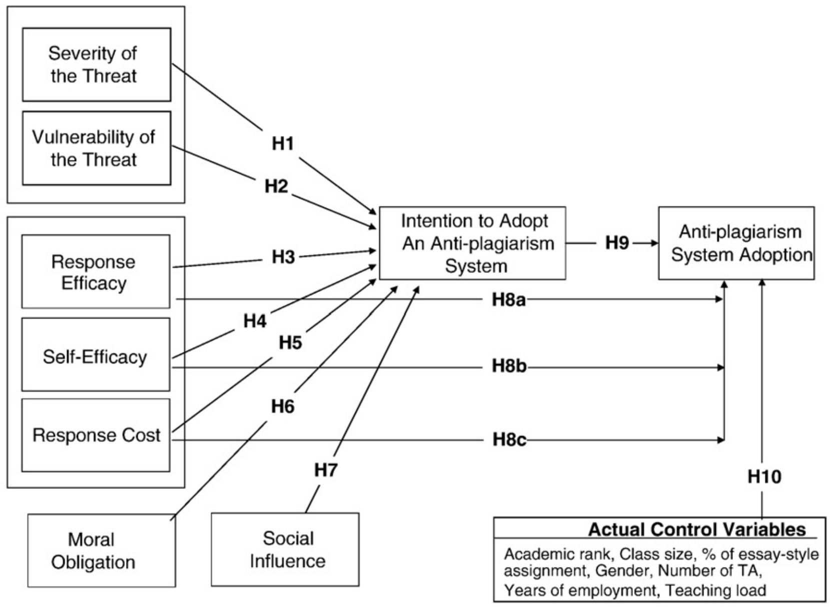

Fig. 1. Research model.

In this context, faculty members should perceive Internet plagiarism as a severe threat because it deteriorates the standards of academic integrity and lowers students' sense of value for honesty, trustworthiness, moral leadership, personal ethics, and civility. Furthermore, Internet plagiarism can instigate imitative plagiarism by peer students who observe Internet plagiarism committed by their classmates, especially if faculty erroneously grants good grades to students who submit copied work because they have not detected it. This scenario could cause significant damage to the faculty members' image if the plagiarism becomes public knowledge. Considering these threats,

H1. Perceived severity positively influences faculty members' intention to adopt anti-plagiarism software.

3.1.2. Vulnerability of the threat

Vulnerability refers to "the conditional probability that the threatening event will occur provided that no adaptive behavior is performed or there is no modification of an existing behavioral disposition" ([55], p.115). The perception of vulnerability pertains to a person's assessment of his or her probability of being exposed to the unfavorable threat [69]. Therefore, the likelihood of adopting the advocated adaptive behavior increases when a person perceives vulnerability as higher. Previous studies reveal significant effects on the intentions to adopt self-examinations for breast cancer [52] and skin cancer [41]. Similarly, this study posits that faculty will seriously consider adopting anti-plagiarism software when they perceive that a class is filled with students who are more inclined to engage in Internet plagiarism. Therefore,

H2. Perceived vulnerability positively influences faculty members' intention to adopt anti-plagiarism software.

3.1.3. Response efficacy

Response efficacy refers to the belief that the adaptive response will work, such that taking the recommended protective action is effective in averting an undesirable threat [18,55]. With information about countermeasures for coping with threats, a person can assess the effectiveness of the advocated adaptive behavior. When he or she perceives response efficacy as higher, the likelihood that the person enacts the adaptive behavior also increases. For example, a person might enroll in a class dedicated to smoking cessation if he or she believes the class will provide an effective means to stop smoking. Response efficacy also has a significant effect on intentions to protect oneself and others [59]. Because anti-plagiarism software represents an effective and efficient tool to detect and deter Internet plagiarism, as well as to educate students about the topic [33], faculty members who perceive they have a high degree of response efficacy and believe that anti-plagiarism software is effective should exhibit a greater intention to adopt the software.

H3. Response efficacy positively influences faculty members' intention to adopt anti-plagiarism software.

3.1.4. Self-efficacy

Self-efficacy refers to the belief that a person is or is not capable of performing a coping behavior [55]. If people have confidence in their ability to conduct a recommended action and perceive the action as not too difficult, they are more likely to adopt it [3,57]. A significant influence of self-efficacy on intentions to take protective actions appears in various behavioral contexts [50]. For example, McClendon and Prentice-Dunn [41] find that self-efficacy increases intentions to stop sunbathing and use sunscreen. The same significant effect of self-efficacy emerges in diverse IS adoption contexts [37]. When faculty members are more convinced of their capability to learn and use anti-plagiarism software and when they believe IT support groups and system providers are available to provide technical support, they should express a greater intention to adopt anti-plagiarism software.

H4. Self-efficacy positively influences faculty members' intention to adopt anti-plagiarism software.

3.1.5. Response cost

Finally, response cost refers to any costs (e.g., monetary, time, effort, inconvenience, unpleasantness, difficulty, complexity, and side effects) associated with taking adaptive actions [54,55]. People hesitate to adopt the recommended actions if they must devote a considerable amount of time, effort, and money to it [23,49]. In addition, if they feel awkward when conducting the recommended actions or encounter resistance from people important to them, they may hesitate [43]. Previous studies indicate a significant negative impact of response costs on adaptive behaviors [27,69], and anti-plagiarism software adoption is no exception. First, faculty must expend extra effort to use the software. For example, as Mulcahy and Goodacre [45] point out, the time required to set up the software is minimal, but reviewing the generated reports requires considerable time. Faculty members also must expend time to redesign the structure of their assignments to use the software and adjust their syllabus to include content associated with Internet plagiarism. Second, the potential for the student–teacher relationship to move from trust to distrust, in response to the increased surveillance, may represent another pertinent cost that makes faculty reluctant to adopt the software. The higher the cost these faculty members perceive, the less likely they are to adopt the anti-plagiarism software. Therefore,

H5. Response cost negatively influences faculty members' intention to adopt anti-plagiarism software.

3.2. Model extension

Although various applications of the PMT receive empirical validation in different behavioral contexts [18], researchers also suggest elaborations, especially for identifying important proximal determinants that may increase its explanatory power [55] or exploring the nomological networks between PMT variables that have yet to be researched. This study extends the PMT in several ways.

3.2.1. Moral obligation

Moral obligation is “an individual's perception of the moral correctness or incorrectness of performing a behavior” [13, p.1441]. It represents a person's perception of his or her responsibility to perform or refuse to perform a certain behavior, which significantly affects ethical human behavioral decision making [35,44]. For example, Lee and Kozar [37] show that moral obligation contributes explains a significant amount of variance in adoption intentions toward anti-spyware software. Thong and Yap [63] indicate that moral judgment affects IS professionals' softlifting. Herath and Rao [28]also found the significant influence of moral obligation on employees' information security behavior. Similarly, this study assumes that faculty defines Internet plagiarism as a morally incorrect behavior and therefore has a responsibility to take proactive actions against it. A faculty member with a higher moral obligation should also exhibit a greater intention to adopt anti-plagiarism software.

H6. Faculty members' high moral obligation relates positively to their intention to adopt anti-plagiarism software.

3.2.2. Social influence

The social pressure to perform a behavior, determined by a person's inclination to comply with people who are important [1] and normative beliefs[28], helps explain adaptive behaviors, both in the field of social psychology [5] and for information technology adoption [31,36,40]. Previous studies of health protection also show that social pressure exerts powerful influences on the initiation, maintenance, and cessation of protective actions [29,50,70]. Therefore, faculty members should have a greater likelihood of adopting anti-plagiarism software if they find their referents either possess a favorable attitude toward adopting the software or already have adopted it. Therefore,

H7. Faculty members are more inclined to adopt the anti-plagiarism software when their referents have a positive attitude towards anti-plagiarism software adoption or have actually adopted the software.

3.2.3. Coping appraisal—actual adoption

Response efficacy, self-efficacy, and response cost are all perceived behavioral control factors that affect the adoption of anti-plagiarism software. This study in turn predicts a direct relationship between these factors and adoption. Previous research reports a significant direct effect of perceived behavioral control variables on actual behavior or behavioral changes [1,2,14]. Specifically, the perceived cost related to a behavior is a strong impediment [17], whereas belief in the ability to complete the behavior and expected outcomes are strong facilitators [3,12].

Even though faculty members likely have strong intentions to adopt anti-plagiarism software, they cannot adopt it if they have too many concerns about a huge potential response cost. Other faculty members can be motivated to adopt the software when they are confident in their capability to learn and use it. Furthermore, faculty members should adopt the software when they believe that its adoption effectively and efficiently will hinder Internet plagiarism and educate students about the legitimate boundary of plagiarism.

H8. Faculty members' assessments of (a) response efficacy, (b) self-efficacy, and (c) response cost significantly influence their adoption of anti-plagiarism software.

3.2.4. Adoption intention—actual adoption

Just as previous studies determine that behavioral intention predicts actual behavior [65], this study predicts that the intention to adopt anti-plagiarism software positively influences actual adoption.

H9. The higher faculty members' intention to adopt anti-plagiarism software, the higher is their actual adoption of the software.

3.2.5. Actual behavioral control

To address the criticism that IT adoption studies mainly investigate factors that affect adoption intention, instead of those that influence actual adoption, some researchers examine the factors that likely influence actual adoption directly. Actual behavioral control is defined as the extent to which a person has the objective skills, resources, and other prerequisites needed to perform a given action [1], which directly affects actual behavior. This study relies on an extensive literature review of research pertaining to actual behavioral control (e.g., [16]), as well as interviews with 11 instructors and university administrators who are knowledgeable about Internet plagiarism and anti-plagiarism software, to identify seven actual control variables that should affect anti-plagiarism software adoption directly. These variables include academic rank, class size, percentage of creative assignments, gender, number of teaching assistants, years of employment, and teaching load.[1] These actual control factors should directly affect faculty's actual adoption of the software, and therefore,

H10. The actual control variable including (a) academic rank, (b) class size, (c) percentage of creative assignments, (d) gender, (e) number of teaching assistants, (f) years of employment, and (g) teaching load affect faculty members' adoption of anti-plagiarism software.

4. Research methodology

To validate measurement instruments for the proposed theoretical model and investigate nomological networks between endogenous and exogenous variables, a questionnaire-based field survey was conducted with faculty members from two large U.S. public universities that have implemented the same anti-plagiarism software since 2001. Two universities have similar institutional cultures in that they are flagship public universities; are located in small college towns in the Midwest; have honor codes; and have faculty absence policy during students' faculty evaluation. The honor codes of those institutions clearly describe the definition of the online plagiarism, procedures and academic sanctions. Turnitin was the target software. It is one of the most popular anti-plagiarism software

[1] The interviews identified a total of 12 factors that might control anti-plagiarism software adoption. The 7 factors selected for this study that were noted at least five times in the 11 interviews.

Table 1
Demographics of target subjects.

Category		Num.	%	Category		Num.	%
Gender	Males	133	61%	# of TA	0	31	14%
	Females	85	39%		1–2	166	76%
Age	Below 30	21	10%		3–4	15	7%
	30–35	48	22%		More than 4	6	3%
	36–40	52	24%	Years of employment	Less than 2 year	37	17%
	41–45	45	21%		2 ≤ years < 4	48	22%
	46–50	31	14%		4 ≤ years < 6	33	15%
	Over 50	21	10%		6 ≤ years < 8	45	21%
Academic rank	Instructor	69	32%		8 ≤ years < 10	21	10%
	Assistant professor	57	26%		Over 10 years	34	16%
	Associate professor	51	23%	Teaching load(# of courses)	1–2	33	15%
	Full professor	41	19%		3–4	150	69%
Class size (# of students)	Less than 20	27	12%		5–6	34	16%
	20 ≤ # < 40	96	44%		7–8	1	0%
	40 ≤ # < 60	69	32%		Over 8	0	0%
	60 ≤ # < 80	3	1%				
	80 ≤ # < 100	2	1%				
	Greater than 100	21	10%				

and has been adopted at half-a-million faculty members and in one hundred ten countries worldwide. To detect the plagiarism, the software examines matches in over 12 billion pages of indexed web content, 100 million students' papers, and over 80,000 professional, academic and practitioner journals and publications. It has been reported to successfully reduce online plagiarism up to 35%.[2] To support faculty members to adopt the software, both institutions provide a self-study tutorial as well as a one-on-one training through either a computer support or a university writing center. Further, they have adopted Blackboard as an instructional tool, and Turnitin software is integrated with the learning system.

The adoption of the software by faculty is voluntary, as was their participation in the survey. An e-mail containing the invitation letter and online questionnaire went out to faculty members, including a brief description of Internet plagiarism and its countermeasures, which gave the potential respondents a better understanding of the context and terminology of the study. Participants were guaranteed anonymity.

A total of 243 faculty members responded. After the removal of 25 incomplete and invalid responses, 218 usable responses appear in the data analysis. The overall response rate is 41%. Actual adoption data come from the universities' teaching and learning centers and writing centers, which operate and manage the software. The respondents represent 15 academic departments and very diverse backgrounds. As Table 1 shows, 133 (61%) were men, and 85 (39%) were women. Sixty-nine respondents indicated they were instructors, 57 assistant professors, 51 associate professors, and 41 of them had attained full professorships. The mean class size for which they were responsible was approximately 57 students. As a mean percentage, creative assignments constituted 62.2%. These respondents had access to an average of 0.8 teaching assistants, had been employed as faculty members for an average of 5.68 years, and taught an average of 3.33 courses per year.

The development of the instruments relied on scientific instrument development processes [61]. The first step involved an extensive literature review pertaining to PTM and IT acceptance. Concurrently, extensive interviews [69] with 11 instructors and university administrators helped clarify and offer insights into anti-plagiarism software adoption rates. The instrument items were operationalized to fit the context of anti-plagiarism software adoption and pretested with eight experts who were familiar with PMT, technology adoption, and instrument development. This process suggested a few revisions to the wording, order of items, content, and format of the questionnaire. Finally, on the basis of a pilot test with 29 faculty members, an exploratory factor analysis revealed several items that did not load well on the factors (i.e., one self-efficacy, one moral obligation) and therefore were removed. Seven-point Likert-type scales measure those constructs. Appendix A shows the final instruments used for this research.

5. Results

The test of the research model uses partial least squares (PLS) analysis, a latent structural equation modeling technique that can simultaneously estimate both the structural model and the measurement model [10]. The PLS-Graph version 3.00 serves to analyze the data.

5.1. Measurement model analysis

The measurement model analysis examines the psychometric properties of the measures for latent constructs, testing for internal consistency, convergent validity, and discriminant validity. Internal consistency represents the extent to which multiple items that propose to measure the same construct generate similar scores. Convergent validity represents the degree to which a measure is correlated with other measures that it is theoretically predicted to correlate with, while discriminant validity refers to the extent to which a construct is not correlated with other constructs that it is theoretically expected not to correlate with [20,61].

The measure of internal consistency uses the composite reliability (CR) index [20]. Composite reliability assesses the overall consistency and repeatability of a collection of heterogeneous but similar measures. Composite reliabilities greater than 0.7 are considered adequate [25].

Table 2 (CR column) shows the internal consistency of each construct, which is well above the cut-off value of 0.7 and meets the recommended criterion. Convergent and discriminant validity receive support from two criteria: the square root of the average variance extracted (AVE) and the standardized item loadings [20]. AVE measures the amount of variance captured by a construct in relation to the variance due to random measurement error. AVE should be at least 0.707 (i.e., AVE > 0.5) and greater than the variance shared between the construct and other constructs in the model, and the standardized item loadings, which should be at least 0.707, such that no measurement item weighs more heavily on other constructs than on the construct it intends to measure. As Table 2 reveals, the tests

[2] http://turnitin.com/resources/documentation/turnitin/sales/Turnitin_Quick_Facts.pdf.

Table 2
Interconstruct correlations.

Construct	CR	α	1	2	3	4	5	6	7	8
1. Vulnerability	0.921	0.874	**0.890**							
2. Severity	0.943	0.918	0.287	**0.897**						
3. Response	0.939	0.902	0.125	0.129	**0.914**					
4. Self-efficacy	0.932	0.895	0.029	0.031	0.217	**0.906**				
5. Response cost	0.939	0.902	−0.022	−0.024	−0.061	−0.134	**0.915**			
6. Moral obligation	0.940	0.904	0.161	0.155	0.336	0.020	0.096	**0.917**		
7. Social influence	0.882	0.839	0.002	0.103	0.045	−0.116	0.072	0.198	**0.890**	
8. Adoption intention	0.979	0.968	0.506	0.538	0.411	0.259	−0.162	0.337	0.090	**0.970**

The values on the diagonal represent the square root of the average variance extracted (AVE).

confirm convergent and discriminant validity. The square root of the AVE for each construct is greater than 0.707, and all constructs share more variance with their own indicators than with those of other constructs. The factor structure matrix (see Table 3) also shows that all indicators exhibit a high weight on their own constructs, with no items weighing more heavily on constructs they were not intended to measure. Finally, all Cronbach's α values of constructs are greater than 0.7, which indicates sufficient reliability.

5.2. Structural model analysis

Table 4 shows the results of the structural model analysis. In line with Wold [68], a bootstrapping test searches for estimates of standard errors to test the statistical significance of path coefficients using *t*-tests [72]. They can explain 59.4% of the total variance in the intention to adopt anti-plagiarism software and 57.3% of variance in actual adoption. Adoption intention (H9: $\lambda = 0.412$, $p < 0.001$), response efficacy (H8a: $\lambda = 0.199$, $p < 0.01$), and four control variables—academic rank (H10a: $\lambda = -0.091$, $p < 0.05$), class size (H10b: $\lambda = -0.203$, $p < 0.01$), percentage of creative assignments (H10c: $\lambda = -0.270$, $p < 0.001$), and gender (H10d: $\lambda = -0.135$, $p < 0.01$)—significantly influence actual adoption. All the major PMT variables have significant effects on adoption intentions. That is, perceived severity (H1: $\lambda = 0.340$, $p < 0.001$), perceived vulnerability (H2: $\lambda = 0.367$, $p < 0.001$), response efficacy (H3: $\lambda = 0.224$, $p < 0.01$), self-efficacy (H4: $\lambda = 0.177$, $p < 0.05$), and response cost (H5: $\lambda = -0.127$, $p < 0.01$) all strongly influence faculty members' intentions to adopt the software. Finally, the effect of moral obligation is significant for adoption intentions (H6: $\lambda = 0.146$, $p < 0.01$), but social influence is not (H7: $\lambda = 0.057$, $p > 0.05$).

6. Discussion and implications

By adopting and extending PMT, this study investigates the facilitators and inhibitors associated with adopting anti-plagiarism software. In turn, it identifies several interesting findings worthy of further discussion.

All threat appraisal and coping appraisal variables significantly affect faculty members' intentions to adopt anti-plagiarism software. That is, the decision of faculty members to adopt software is influenced by the perceived magnitude of the negative consequences of Internet plagiarism and its likelihood in their classes, as well as the expected benefits of adopting the anti-plagiarism software, their own capability to adopt the software, and the expected cost associated with the adoption. Two threat appraisal variables have particularly strong effects on intentions to adopt, which suggests that threat appraisals are more influential in the context of this study. Yet IT acceptance researchers have treated this software similar to a productivity-enhancing technology and adopted generic IT adoption theories to address its adoption, which meant they overlooked threat variables. Because the main objective of adopting protection systems appears to be an effort to reduce a threat, research should include threat variables to investigate the adoption of diverse protection systems.

This model extension also examines whether coping appraisal variables might directly influence software adoption; only response

Table 3
Factor structure matrix of loadings and cross-loadings.

	Items	1	2	3	4	5	6	7	8
1. Vulnerability	Vul1	**0.881**	0.252	0.132	0.012	−0.061	0.093	0.056	0.383
	Vul2	**0.910**	0.400	0.120	0.028	−0.011	0.218	0.110	0.435
	Vul3	**0.886**	0.364	0.156	0.028	−0.030	0.170	0.113	0.513
2. Severity	Sev1	0.406	**0.893**	0.157	0.143	−0.041	0.146	0.158	0.465
	Sev2	0.297	**0.898**	0.071	−0.016	−0.051	0.117	0.163	0.424
	Sev3	0.372	**0.924**	0.062	0.058	0.029	0.134	0.185	0.370
	Sev4	0.284	**0.874**	0.066	0.101	0.079	0.168	0.192	0.388
3. Response efficacy	RE1	0.127	0.069	**0.896**	0.104	−0.058	0.279	0.032	0.337
	RE2	0.141	0.080	**0.936**	0.161	−0.114	0.290	0.084	0.412
	RE3	0.153	0.136	**0.910**	0.154	−0.050	0.312	0.051	0.359
4. Self-efficacy	SE1	0.065	0.096	0.207	**0.941**	−0.204	0.069	−0.048	0.302
	SE2	0.011	0.055	0.060	**0.896**	−0.076	0.022	−0.094	0.202
	SE3	−0.037	0.061	0.120	**0.878**	−0.156	−0.071	−0.154	0.161
5. Response cost	RC1	−0.015	0.011	−0.040	−0.138	**0.938**	0.114	0.088	−0.192
	RC2	−0.018	0.077	−0.109	−0.149	**0.910**	0.097	0.058	−0.144
	RC3	−0.063	−0.066	−0.089	−0.174	**0.896**	0.065	0.051	−0.196
6. Moral obligation	MO1	0.145	0.094	0.268	−0.015	0.082	**0.919**	0.207	0.325
	MO2	0.185	0.169	0.298	0.053	0.100	**0.930**	0.124	0.368
	MO3	0.169	0.168	0.313	0.020	0.088	**0.899**	0.161	0.327
7. Social influence	SI1	0.150	0.227	0.044	−0.069	0.076	0.153	**0.998**	0.194
	SI2	−0.007	0.091	0.095	−0.138	0.050	0.200	**0.766**	0.088
8. Adoption intention	INT1	0.519	0.454	0.391	0.258	−0.229	0.385	0.189	**0.968**
	INT2	0.475	0.447	0.411	0.262	−0.179	0.348	0.129	**0.966**
	INT3	0.474	0.460	0.385	0.236	−0.162	0.355	0.177	**0.975**

Table 4
Results of structural model analysis.

Hypotheses	Path coefficients	t-value
Intention $R^2 = 0.564$		
H1: Perceived severity → intention	0.340***	6.025
H2: Perceived vulnerability → intention	0.367***	7.831
H3: Response efficacy → intention	0.224***	3.987
H4: Self-efficacy → intention	0.177**	3.051
H5: Response cost → intention	−0.127**	2.882
H6: Moral obligation → intention	0.146**	2.601
H7: Social influence → intention	0.057	1.067
Adoption $R^2 = 0.606$		
H8a: Response efficacy → adoption	0.199***	3.638
H8b: Self-efficacy → adoption	−0.058	1.190
H8c: Response cost → adoption	−0.001	0.021
H9: Adoption intention → adoption	0.412***	7.531
H10a: Academic rank → adoption	−0.091*	1.981
H10b: Class size → adoption	−0.203**	3.259
H10c: Percentage of creative assignments → adoption	−0.270***	5.579
H10d: Gender → adoption	−0.135**	2.834
H10e: Number of TAs → adoption	0.071	1.235
H10f: Years of employment → adoption	0.008	0.157
H10g: Teaching load → adoption	0.004	0.092

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

efficacy, not self-efficacy and response cost, has a significant, direct influence on actual adoption. Therefore, faculty members appear motivated to adopt the software when they perceive a high expected return on investment; faculty awareness programs and educational materials pertaining to Internet plagiarism should emphasize the benefits of anti-plagiarism software adoption. The insignificance of the self-efficacy and response cost variables may reflect the stronger influence of the actual control variables compared with perceived control variables. The low correlation between self-efficacy and actual adoption ($r = 0.102$) and between response cost and actual adoption ($r = -0.087$) indirectly supports this interpretation.

Several actual control variables have significant direct influences on software adoption. The significant negative effect of academic rank suggests that the higher the rank of faculty members, the more reluctant they are to adopt the software. Faculty members with a higher academic rank tend to be somewhat older, more conservative, and less IT savvy, which may make them reluctant to adopt new technologies in their classes. The negative effect of class size on adoption seems counterintuitive though, in that smaller class sizes prompted more adoption. Faculty members who teach larger classes might not adopt the software because they employ curricula that are standardized and feature mostly non-essay assignments, for the sake of grading convenience. A significant negative effect of the percentage of creative assignments seems reasonable, considering the lower chances to plagiarize creative assignments such as programming or essay articles. Therefore, the demand for anti-plagiarism software declines when courses include many creative assignments. Finally, men are more likely to adopt the software, consistent with previous findings pertaining to IT adoption that show women are generally risk averse, more concerned with their capability to adopt new technology, and likely to avoid advanced technology [58].

Moral obligation facilitates the adoption of anti-plagiarism software; faculty members appear to consider Internet plagiarism a serious, morally incorrect behavior and feel pressure to adopt countermeasures. Not adopting the software might increase Internet plagiarism in the classroom, thus deteriorating overall academic integrity. Honest students recognize the Internet plagiarism committed with impunity by other students and feel a temptation to mimic such plagiarism. The debriefing interviews revealed an interesting moral dilemma for faculty with regard to adopting the software: They expressed serious concerns that the commercial anti-plagiarism software vendors might misuse the materials submitted to check for Internet plagiarism. To reduce this concern, diverse protection mechanisms that prevent the misuse of the software, including legal contracts with software vendor, should be enforced. In addition, the findings require some caution in their interpretation, in that adoption is a desirable behavior, but not adopting the software is not necessarily a morally incorrect behavior. Some faculty members may adopt different, equally effective means to prevent Internet plagiarism in their classes.

Contrary to expectations, social influence has an insignificant effect, which implies that faculty members do not seriously consider others' adoption of or attitude toward anti-plagiarism software. Those in academe tend to value academic freedom and thus may make more independent decisions, even for important matters. The voluntary adoption of the software also might affect this insignificance finding, which would match previous IT acceptance studies [65].

This study contains several limitations. First, the faculty members come from two U.S. public universities, and though the respondents represent 15 diverse departments, it would be preferable to recruit subjects from more universities to generalize the findings of this study. In particular, recruiting subjects from colleges or universities that represent specific institutional types (e.g., teaching versus research-focused) or have a unique culture (e.g., religious versus secular school) could further generalize the findings. Second, this study does not examine the relationship between adoption and outcomes, namely, whether adoption reduces Internet plagiarism in the classroom. Longitudinal studies should investigate such complete nomological networks.

In addition to research to address these limitations, several other promising research streams appear evident. For example, this study proposes and validates a theoretical model that adopts PMT to identify factors affecting the adoption of protective software and considers threat appraisal variables that have not been investigated previously. Without access to such theory, previous studies use general IT adoption theories to address the adoption of protective software, an approach that ignores important threat appraisal variables. The PMT offers a tool to understand an interesting phenomenon in a systematic way; the previous paucity of a theory of protective software adoption appears to relate directly to incomplete, inconsistent, or misleading understanding of the adoption phenomenon. Thus, the separate attention to developing theories for protective software adoption is worthwhile. As a part of the theory development, this study also has attempted to extend the original PMT theory and successfully demonstrates that the expanded model, with social influence, moral obligation, and actual control variables, explains much of the variance in the adoption of anti-plagiarism software. Thus, the model expansion appears to provide a valuable effort, and the expanded model can provide a theoretical foundation for protective actions in various behavioral contexts, including the adoption of protective software. This study also appears to be the first attempt to view the phenomenon of Internet plagiarism from the perspective of educators who play a critical role in counteracting it. In contrast with previous studies, primarily focused on understanding the motivation of students who committed Internet plagiarism, this investigation observes the same phenomenon from the perspective of faculty members who must cope with plagiarism by adopting countermeasures. The limits of attention to malicious actors rather than protectors has provoked considerable criticism in the IT security area; this study contributes to broaden attention to both the spear (e.g., hackers) and the shield (e.g., IT personnel) to discover more effective solutions to malicious actions.

From a practitioner perspective, this study provides intriguing information to vendors of anti-plagiarism software and university administrations, which should prepare customized educational materials for faculty members that effectively address both the risk of Internet plagiarism and the efficacy of anti-plagiarism software.

Because both threat and coping appraisals significantly affect the adoption of anti-plagiarism software, promotional campaigns should address both appraisals. More emphasis on threat appraisals could motivate the adoption of anti-plagiarism software more powerfully. Promotional materials also may be customized to attract faculty members according to the actual control factors that directly influence their adoption of the software. For example, for senior female faculty members, the campaign should include information emphasizing the ease of implementation.

The findings of this study also might assist university administrators develop a strategy that increases adoption rates of the software. For example, the university might offer a one-to-one tutorial program for faculty members to enable their use of the software. To reduce the adoption costs perceived by faculty members, including deteriorated relationships with students and malicious use of submitted assignments, university administrations should provide an educational session for students, as part of their orientation programs, and institute a legal contract with software vendors to prevent any misuse of materials sent by faculty members.

In summary, this study, by adopting and expanding the protection motivation theory, identifies several factors that motivate or inhibit faculty members' anti-plagiarism software adoption. By persuading and motivating faculty members to adopt the software, in connection to other initiatives to counteract Internet plagiarism, universities and colleges can maintain a higher degree of academic honesty.

Appendix A. Instrument items

Perceived vulnerability [15]

PV1 My class could be vulnerable to Internet plagiarism.
PV2 My class could be susceptible to Internet plagiarism.
PV3 Students in my class are likely to commit Internet plagiarism.

Perceived severity [69]

PS1 Internet plagiarism may seriously undermine the standards of academic integrity.
PS2 Internet plagiarism committed by classmates influences honest students to imitate their behavior.
PS3 There is a high chance for me to provide good grades to those who plagiarize without detecting their plagiarism.
PS4 My image will be seriously damaged if the plagiarism committed in my class is publicized.

Response efficacy [69]

RE1 Adopting anti-plagiarism software will deter my students from committing Internet plagiarism.
RE2 Implementing anti-plagiarism software in my class is an effective way of detecting Internet plagiarism.
RE3 Enabling the anti-plagiarism software in my class is an effective way to educate about the boundary of Internet plagiarism.

Self efficacy [12]

SE1 It would be easy for me to use the anti-plagiarism software by myself.
SE2 I could adopt the software even though there is no one around to tell me what to do as I go.
SE3 I could adopt the anti-plagiarism software if I could contact someone if I got stuck.

Response cost [62]

RC1 There is too much overhead associated with the adoption of the anti-plagiarism software in my class.
RC2 It takes a considerable amount of time and effort to be familiar with and use anti-plagiarism software.
RC3 The use of the anti-plagiarism software may cause distrustful relationships between me and students.

Social influence [50]

SI1 Most people whose opinions I value do not adopt anti-plagiarism software.
SI2 Most people who are important to me do not value the adoption of the anti-plagiarism software.

Moral obligation [5]

MO1 If my colleagues do not take any actions to counteract Internet plagiarism, it is my duty to persuade them to adopt them.
MO2 I think I have to take actions to cope with Internet plagiarism if it deteriorates academic integrity of my institution.

Adoption intention [66]

INT1 I intend to use the anti-plagiarism software.
INT2 I predict I will use the software in the near future.
INT3 I plan to use the software in the near future.

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