[Journal of Information Systems Education](https://aisel.aisnet.org/jise)

Volume 35 | Issue 4 Article 8

12-15-2024

Understanding the Impact of Perceptions of Student Assessment Congruence, Satisfaction, and Peer Behavior on Cheating Incentive in Higher Education

Josey Chacko
Mount St. Mary's University, chacko@msmary.edu

Stephane E. Collignon
West Virginia University, stephane.collignon@mail.wvu.edu

Christina L. Green
Mount St. Mary's University, c.l.green@msmary.edu

A. Graham Peace
West Virginia University, Graham.Peace@mail.wvu.edu

Recommended Citation

Chacko, Josey; Collignon, Stephane E.; Green, Christina L.; and Peace, A. Graham (2024) "Understanding the Impact of Perceptions of Student Assessment Congruence, Satisfaction, and Peer Behavior on Cheating Incentive in Higher Education," *Journal of Information Systems Education*: Vol. 35 : Iss. 4 , 481-494.
DOI: https://doi.org/10.62273/CSGL6637
Available at: https://aisel.aisnet.org/jise/vol35/iss4/8

Journal of Information Systems Education

Volume 35
Issue 4
Fall 2024

Understanding the Impact of Perceptions of Student Assessment Congruence, Satisfaction, and Peer Behavior on Cheating Incentive in Higher Education

Josey Chacko, Stephane E. Collignon, Christina L. Green, and A. Graham Peace

Recommended Citation: Chacko, J., Collignon, S. E., Green, C. L., & Peace, A. G. (2024). Understanding the Impact of Perceptions of Student Assessment Congruence, Satisfaction, and Peer Behavior on Cheating Incentive in Higher Education. *Journal of Information Systems Education*, 35(4), 481-494. https://doi.org/10.62273/CSGL6637

Article Link: https://jise.org/Volume35/n4/JISE2024v35n4pp481-494.html

Received:	December 30, 2023
First Decision:	February 18, 2024
Accepted:	May 28, 2024
Published:	December 15, 2024

ISSN: 2574-3872 (Online) 1055-3096 (Print)

Journal of Information Systems Education, 35(4), 481-494, Fall 2024
https://doi.org/10.62273/CSGL6637

Understanding the Impact of Perceptions of Student Assessment Congruence, Satisfaction, and Peer Behavior on Cheating Incentive in Higher Education

Josey Chacko
Richard J. Bolte, Sr. School of Business
Mount St. Mary's University
Emmitsburg, MD 21727, USA
chacko@msmary.edu

Stephane E. Collignon
John Chambers College of Business and Economics
West Virginia University
Morgantown, WV 26506, USA
stephane.collignon@mail.wvu.edu

Christina L. Green
Richard J. Bolte, Sr. School of Business
Mount St. Mary's University
Emmitsburg, MD 21727, USA
c.l.green@msmary.edu

A. Graham Peace
John Chambers College of Business and Economics
West Virginia University
Morgantown, WV 26506, USA
graham.peace@mail.wvu.edu

ABSTRACT

Student cheating is a growing concern in all aspects of higher education, particularly in technical programs such as information systems. Technology is also enabling student cheating. This paper utilizes existing literature and various behavioral theories, including incentive theory, the theory of planned behavior, social reciprocity theory, expected utility theory, and deterrence theory to develop a model of cheating incentive in students. The model was tested using a survey of 245 undergraduate students in a decision sciences class at a large US land-grant university, with the results showing that the incentive to cheat is predicted by the student's satisfaction with the assessment process and observed cheating by peers. Perceived evaluation congruence (the perception of the student that the exam measures knowledge of the course material) was, in turn, found to be a precursor of satisfaction. Many institutions focus on increasing the risk of being caught and punished, but focusing on the student's satisfaction with the assessment process as a way of reducing the incentive to cheat is also key. This may begin a virtuous cycle, where greater congruence between the class material and the assessment mechanism leads to greater satisfaction with the assessment, which leads to a reduction in the incentive to cheat. This, in turn, leads to more valid testing data for the instructor, which leads to even greater congruence and satisfaction. The reduction in individual cheating will lead to a reduction in observed cheating, lowering the incentive to cheat even further.

Keywords: Academic integrity, College students, IS education research, Learning assessment, Student attitudes, Student satisfaction

1. INTRODUCTION

Cheating has long been a cause of concern on college campuses. The infamous 2012 scandal at Harvard University, in which over half the class of 279 students were caught cheating, and the recent 2021 United States Naval Academy case where at least 100 midshipmen cheated on a Physics final exam, are sobering examples of bright young students involved in academic dishonesty (Lang, 2013; Toropin, 2021). This issue is not limited to elite institutions, and increased cheating on campuses of all types was reported during the COVID-19 pandemic, including rates more than double the norm at institutions such as Virginia Commonwealth University and the University of Georgia (Dey, 2021). At the University of Missouri, 150 students were caught cheating in an online class in 2020 (Williams, 2020). It is possible that actual cheating rates have remained constant and the increase in observations is due to improved detection, but the fact remains that cheating appears to be rampant.

This issue is of significant relevance to information systems (IS) faculty for two reasons. Firstly, cheating is particularly acute in classes that focus on technical mastery (Newstead et al., 1996), such as typical information systems classes. Studies indicate that business and engineering students are more likely to cheat than students in other majors, and even more so at the graduate level (McCabe et al., 2006; Smyth & Davis, 2004). The prevalence of academic dishonesty in business schools is particularly worrisome because it is a predictor of unethical behavior in the workplace (Ballantine et al., 2018; Klein et al., 2007; Lawson, 2004; Premeaux, 2005; Sims, 1993; Smith et al., 2021). Secondly, technology, the main focus of any IS program and a powerful tool for advancing both business and education, has proven to be an enabler for the newer wave of academic dishonesty. "E-cheating" can range from students using the Internet to find answers, to the unauthorized use of cell phones in classes and while taking exams (Bain, 2015). Technology facilitated the massive move to online courses during the COVID-19 pandemic, but studies show that the majority of students believe that cheating is easier in an online environment (King et al., 2009). The advent of publicly available Generative AI tools has significantly increased the concern regarding academic dishonesty in higher education, with one faculty member quoted as saying "we're in full-on crisis mode" (Grecker & Associated Press, 2023). This is particularly concerning in the IS field, where technical skills such as programming can be replicated by students using online AI tools. The ensuing "arms race" of responses, from firms offering AI detection services to those offering detector avoidance services, is the new norm (Oravec, 2023). As a result, some faculty are moving back to in-class paper tests (D'Agostino, 2023; Shaw, 2022). Multiple-choice question (MCQ) exams, in particular, continue to be a popular testing instrument, due to their efficiency and objectivity (Liu et al., 2023).

Several reasons have been identified as to *why* students cheat. Some students believe that exams are unfair (Genereux & McLeod, 1995; Murdock, 1999). Some are simply unprepared for the exam or feel pressure from parents and peers (Davis et al., 1992; Owunwanne et al., 2010). Faculty have received part of the blame, with lack of instructor vigilance found to be a contributing factor (Genereux & McLeod, 1995). This has led to various actions being suggested to mitigate academic dishonesty, including directed learning approaches (such as deep learning) (Ballantine et al., 2018), content coverage (business ethics) (Ritter, 2006), adjusting the academic environment (such as the adoption of honor codes) (Trevino et al., 1998), increased instructor vigilance (Genereux & McLeod, 1995; Owunwanne et al., 2010), redesign of the physical environment (such as seating arrangements, elimination of electronic devices) (Davis et al., 1992; Fendler et al., 2018; Owunwanne et al., 2010), and improved design of testing instruments (Samuel & Hinson, 2013).

This paper focuses on the factors that impact a student's *incentive* to cheat. Utilizing incentive theory and other behavioral frameworks as a foundation, we develop a model to identify the factors that impact a student's cheating incentive, with the goal of providing guidance regarding how to improve cheating behavior by reducing the student's incentive to commit academic dishonesty. In the following sections, the paper will discuss the literature in the area of cheating motivations and dissuaders for students in higher education, detail a proposed model of cheating incentive and four corresponding hypotheses, and provide support for the model through the analysis of a survey of undergraduate business school students taking a decision sciences course in an IS/MIS type program. We conclude with a discussion of the results, practical advice for faculty, and suggestions for future research.

2. LITERATURE REVIEW

Academic dishonesty is clearly a significant problem on college campuses, with both formal and informal research consistently showing significant levels of cheating amongst undergraduate college students (McCabe, 2005; Owunwanne et al., 2010). To better understand why students cheat, and how to manage the issue, we reviewed several theories aimed at explaining human behavior, focusing on what provides a student with an incentive to cheat or not cheat.

Incentive Theory posits that rewards and punishments are the primary motivators of behavior (Ryan & Edward, 2000). In his work *The Behavior of Organisms*, Skinner (1938) argued that individuals are incentivized to act based on the external factors of deprivation, satiation, and aversive stimulation. More recent literature finds that incentives can be intrinsic, such as internal feelings, or extrinsic, such as rewards and compensation (Morris et al., 2022). The greater the individual's incentive to commit a behavior, the more likely it is that they will act. Kajackaite and Gneezy (2017) found that an increase in the incentive to lie was correlated with increased lying, indicating a link from incentive to socially undesirable behavior.

While not directly addressing incentive, the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) posits that the intention to undertake a specific behavior is the best predictor of whether or not an individual will actually commit the behavior. Intent, in turn, is predicted by subjective norms, and the attitude towards the behavior. The more an individual believes the behavior is accepted and supported by their social group, and the more positively the individual perceives the behavior, the greater the intent of the individual to participate in the behavior. Ajzen (1991) expanded TRA by including the concept of perceived behavioral control (PBC), thus creating the Theory of Planned Behavior (TPB). PBC refers to the individual's belief in their ability and opportunity to commit the behavior in question. The greater the individual's belief in their ability to commit the act, the greater their intent to do so. Ajzen (1969), for example, posited that the opportunity to cheat is a factor in the act of cheating.

Witnessing others cheating impacts a student's opinion on whether cheating is unethical. In a study using both TRA and TPB to predict intentions for academic cheating in higher education across seven countries, Chudzicka-Czupała et al. (2016) found that seeing others cheat makes an individual view their own cheating as less wrong. Students are also more likely to cheat on exams if they engage in other forms of cheating (Kremmer et al., 2007).

The relationship between assessment design and cheating is complex, as it is affected by individual and contextual factors (Bretag et al., 2019). Kincaid and Zemke (2006) found that assessment congruence is related to student satisfaction with the test format; if students perceive that the assessment tool is congruent with the materials on which they are being tested, then they are more satisfied with the assessment and less likely to cheat. This is supported by Social Reciprocity Theory (SRT), which posits that people respond positively to behavior they deem to be positive, and negatively to behavior they deem to be negative (Gouldner, 1960). If students perceive their tests to be difficult, or have negative perceptions towards the assessment, it influences the desire to cheat (Passow et al., 2006; Wenzel & Reinhard, 2020). Testing format dissatisfaction also causes students not to see the relevance of the assessment and leads to disengaged and disinterested students (Jones & Egley, 2004). Perceived fairness is related to the student's satisfaction with the assessment. Students find assessments satisfactory when they are perceived to be fair (Wygal et al., 2017). MacGregor and Stuebs (2012) found that "students are able to justify unacceptable behavior if they believe their peers have an unfair advantage" (p. 265). Similarly, Kincaid and Zemke (2006) found that the perception of unfair testing can influence cheating behavior. McCabe et al. (2001) argued that cheating can be dissuaded through the development of a fair form of assessment, while lab experiments have shown that individuals who feel they are unfairly treated are more likely to cheat in the next game they play: "Experiencing a norm violation justified the violation of another norm" (Houser et al., 2012, p. 1645).

Kohlberg's (1981) moral reasoning theory (preconventional, where morality is determined by the consequences for the individual; conventional, where morality is determined by social rules; and postconventional, where morality is determined by core values) focuses primarily on moral and ethical judgment—or in other words, how people think about and decide what course of action is morally or ethically right. Kohlberg suggests that moral reasoning development can occur through training. However, it typically occurs through interaction with peers and situations that contradict their way of thinking. If students are held accountable for cheating, vicarious/social learning should create awareness for other students who may be told about the consequences. This is particularly valid, since students are at the preconventional development stage (obedience and punishment orientation). This adds evidence that the role of peer observation is a factor in behavior, as also posited by TRA and TPB.

Finally, from economic theory and criminal justice literature, we find the related concepts of Expected Utility Theory (EUT) and Deterrence Theory. EUT posits that an individual will calculate the expected utility of an action and choose the course that maximizes the outcome in their favor, when faced with risky decisions (Schoemaker, 1982). If a student determines that the benefits of cheating outweigh the potential negative consequences of the action, then it is in their best interest to cheat. This is related to Deterrence Theory, which posits that as the perceived risk of being caught (punishment certainty), and the perceived level of punishment (punishment severity) increase, the less likely it is that the individual will carry out the behavior (Tittle, 1980). Ehrlich (1996) linked these deterrence factors to economic theory, essentially putting them in the context of EUT. Peace et al. (2003) utilized both theories to find that the costs of punishment certainty and punishment severity were factors in the expected utility calculation of individuals contemplating the dishonest act of software piracy.

In summary, various theories exist to explain and predict human behavior (see Table 1). However, several themes stand out. Observed peer behavior, satisfaction with the testing instrument, perceived assessment congruence, risk aversion, and perceived costs (punishments) and benefits, all play a part in the individual's incentive to commit an act such as academic dishonesty.

Theory	Description
Incentive Theory	Rewards and punishments, including both intrinsic and extrinsic factors, are the primary motivators of behavior (Morris et al., 2022; Ryan & Edwards, 2000; Skinner, 1938)
Theory of Reasoned Action (TRA)	Intention predicts behavior. Intention, in turn, is predicted by subjective norms and attitude towards the behavior (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975)
Theory of Planned Behavior (TPB)	TRA with the addition of perceived behavioral control (PBC) as a precursor of intention (Ajzen, 1991)
Social Reciprocity Theory (SRT)	People respond positively to behavior they deem to be positive, and negatively to behavior they deem to be negative (Gouldner, 1960)
Moral Reasoning Theory	Moral reasoning development typically occurs through interactions with peers and situations that contradict the individual's way of thinking (Kohlberg, 1981)
Expected Utility Theory (EUT)	An individual will calculate the expected utility of an action and choose the course that maximizes the outcome in their favor (Schoemaker, 1982)
Deterrence Theory	The perceived risk of being caught (punishment certainty) and the perceived level of punishment (punishment severity) impact the decision to commit the act (Tittle, 1980)

Table 1. Summary of Theories Utilized

3. HYPOTHESES DEVELOPMENT

We propose a model of cheating incentive in college students as detailed in Figure 1.

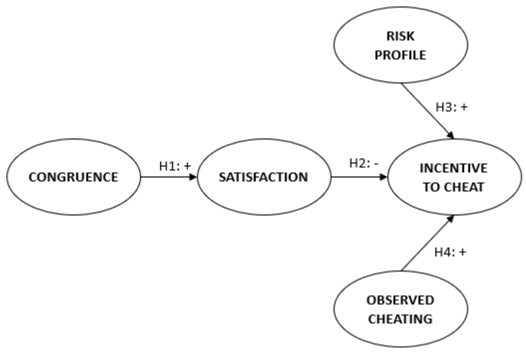


Figure 1. A Model of College Student Cheating Behavior

At the core of the model is the proposal that risk profile, satisfaction with the assessment tool, and the observance of cheating by fellow students are all precursors of the incentive to cheat. In turn, assessment congruence is posited to be a precursor of satisfaction.

Using the common themes identified in the literature above, four testable hypotheses were developed. Each contributes to the model of cheating incentive.

Congruence of students' learning experiences and the assessment format (assessment congruence) can play an important role in determining how satisfied students may feel about the assessment tool (Kincaid & Zemke, 2006). If students believe that an exam is testing them on materials that they have learned in the class, it makes sense that they will be more satisfied with the exam, as opposed to an exam that is not in congruence with the course material. We therefore propose:

H1: Perceived assessment congruence is positively related to satisfaction with the assessment tool.

Wenzel and Reinhard (2020) found that a student's negative perception of the measurement instrument will positively influence their desire to cheat. Social Reciprocity Theory lends credence to this claim, with its assertion that people respond negatively (cheating) to behavior they deem to be negative (an exam with which they are dissatisfied) (Gouldner, 1960). Similarly, testing format dissatisfaction causes students not to see the relevance of the assessment and leads to disengaged and disinterested students (Jones & Egley, 2004). We therefore propose:

H2: Satisfaction with the assessment tool is negatively related to incentive to cheat.

Committing academic dishonesty involves the risk of being caught and punished. Peace et al. (2003) utilized Deterrence Theory and Expected Utility Theory to find that the perceived certainty of being caught for committing software piracy directly impacted an individual's attitude towards the behavior and also the individual's perception of their ability to commit the behavior. In the case of cheating, we posit that the student's risk profile (i.e., the willingness to take on more risk) is positively related to their incentive to cheat. Therefore, we propose:

H3: Risk profile is positively related to incentive to cheat.

Rettinger and Kramer (2009) found that "cheating is contagious," with knowledge of other students' cheating being the single biggest predictor of cheating behavior. Similarly, Chudzicka-Czupała et al. (2016) found that seeing others cheat makes an individual view their own cheating as less wrong. This may be related to the issue of fairness. MacGregor and Stuebs (2012) found that students who believed that their peers had an unfair advantage were more likely to cheat themselves. As said by a student, "When everybody is cheating and getting good grades, it makes you want to do it too because obviously, everyone wants good grades" (Shaw, 2022, p. 1). Moral reasoning development often occurs through interaction with peers, while peer norms are an integral part of the Theory of Planned Behavior's predictor of behavior. Consequently, we use these theories to propose:

H4: Observed cheating behavior is positively related to incentive to cheat.

4. METHODOLOGY AND DATA COLLECTION

We set our study in an undergraduate decision sciences course offered by the Business Information Technology/Management Information Systems department at a land-grant university in the mid-Atlantic region of the United States. The course was offered via three sections in a face-to-face format. The instructors of this course traditionally used MCQ tests but faced issues with both providing useful feedback and academic dishonesty, as is common in a large section in a full classroom. To prevent cheating, four different versions of the test were usually distributed to students. Each version shared at most 70% of its questions with another version, and the questions, as well as the choices, were randomized. Nevertheless, because some questions were graphical, it was often possible for students to identify the questions that were the same on differing text versions. Therefore, despite dissuasive measures, cheating still occurred. It should be noted that students were made aware of the institution's policies on cheating and plagiarism at the beginning of the semester, as recommended by Trevino and Nelson (2021).

4.1 Survey Questionnaire Development

The survey questionnaire is provided in Appendix A. In this section, we explain how the measurement items were constructed.

4.1.1 Satisfaction. Two sources were used to build this construct in the questionnaire. In the first, Whiting et al. (2008) built a survey questionnaire in which employees of a company answered if they were satisfied with their performance assessment system. The questionnaire mixed the notions of satisfaction and fairness as per our a priori observation, with items such as: "My current performance appraisal system is fair," and "I am satisfied with my current performance appraisal system." Ling and Libby (2010) surveyed students regarding how satisfied they were with an assignment format, using such items as "I like this type of individual assignment more than the traditional form of assignment." Items from Whiting et al. (2008) that were not relevant to our study or that did not load with satisfaction as shown by Ling and Libby (2010) were removed. Our final construct was composed of five items measuring how students liked the test format (OS2), how they found it satisfactory (OS1), and how fair they found the test to be (FA1, FA2, and FA3).

4.1.2 Assessment Congruence. Whiting et al. (2008) developed an instrument to assess employee-perceived performance appraisal congruency. The items from our questionnaire are inspired by their work. In industry, people are evaluated on what tasks they perform. In a MCQ context, students are evaluated on what they know. We thus equate knowing the course material to performing tasks well. As a result, our construct is composed of three items relating to knowledge. Items CO1 and CO3 state that the test format rewards knowing the answers. Item CO2 states that the test format rewards knowing the class material.

4.1.3 Risk Profile. The purpose here was to build a construct that captures a trait of personality that is independent of context. As such, we opted for items from a Domain-Specific Risk-Taking (DOSPERT) scale (Blais & Weber, 2006; Coppola, 2014) and mixed items related to risk taking in general (RP1) and in different situations—recreational (RP2), and financial (RP3). RP3 is a reversed item. The inclusion of reverse items is a common but debated practice. It can cause issues such as decreased reliability of a variable, and lower fit of the model (Hughes, 2009). However, it can act as a survey "speed bump" (Podsakoff et al., 2003), slowing down respondents when they answer questions, thus allowing for more intentional thinking.

4.1.4 Incentive to Cheat. The incentive to cheat is a highly contextual construct. We did not find prior works that provided useful tools for measuring this factor. Because of our experience with behavioral studies, and following general guidelines, we chose to develop an ad hoc scale. Incentive to cheat is composed of three items. One item asks if students are encouraged to cheat (CH2). Two items ask if the respondents agree that there is no incentive or no influence toward cheating (CH1 and CH3). As explained in the discussion of the risk profile scale, mixing reverse and forward items can help capture more variability. Since "incentive to cheat" is our dependent variable, we are interested in capturing as much meaning as we can.

4.1.5 Observed Cheating. We could also find no previously validated items for measuring observed cheating. Again, using best practices and our experience with behavioral studies, an observed cheating measurement was developed consisting of two items, capturing whether students saw cheating occur (CH4) or were told about cheating occurring (CH5).

4.2 Data Collection and Sample

The exam format we utilized as a context for the study followed a validated MCQ format (Collignon et al., 2020). Appendix A provides details on the format and shows how students were prompted. We surveyed our students immediately after the second comprehensive exam of the semester in a decision sciences course. Students were provided time during class to fill out the survey, which also remained open for four days following the exam. The survey was approved by our university's institutional review board (IRB), and students were assured that their answers would remain anonymous and would not interfere with their results on the test. Completing the survey was not rewarded in any way, so as to remove any perception that students could answer in a way to please the research team (and their instructor).

Other techniques covered by Podsakoff et al. (2003) to reduce common method bias were employed. As explained earlier, some survey items within a set of similar items were reversed so as to avoid conveying a phrasing bias (Weijters et al., 2013). The questions on the survey were randomized, and one question served as an attention check to control whether students were indeed reading questions when answering.

Out of 289 students who were taking the class, 277 students opened the survey. However, 32 did not answer all questions or pass the attention check, yielding 245 valid responses and a response rate of 84.8%. Descriptive statistics can be found in Table 2.

4.3 Exploratory Factor Analysis: Measurement Model Testing

All analyses were conducted with SPSS and AMOS 28. The five constructs in the research model were developed based on the literature, but exploratory factor analysis (EFA) was also used to confirm that the measurement items empirically loaded properly on these constructs. We made sure that all statistical indicators indicated an EFA could be conducted. None of the items displayed collinearity issues, all correlations in the item correlation matrix were satisfactorily below 0.8, and the determinant of the matrix was 0.003, satisfactorily above the 0.00001 threshold (Field, 2024). Bartlett's test of sphericity was statistically significant, indicating that some items should load together on common factors. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.753. This is "middling" level by Kaiser's standards (Kaiser & Rice, 1974). This level falls short of being "meritorious" (when above 0.8) but also is far from being below 0.6, which would require remedial action. The EFA was performed with Promax rotation (other rotation methods yielded similar results but Promax is recommended when correlations between factors are expected). The pattern matrix showed all items loading together as conceptualized, except for item CH2 of the Incentive scale.

Descriptive	Ethnicity	College year
Mean age: 20.8 Male: 154 (63%) Female: 91 (37%) Self-determined: 0	White/Caucasian: 180 (73%) Asian: 40 (16%) Black/African Am.: 7 (3%) Middle Eastern: 7 (3%) Latino: 5 (2%) Other: 6 (3%)	Freshman: 1 Sophomore: 70 (29%) Junior: 143 (58%) Senior: 29 (12%) Other: 3 (1%)

Table 2. Sample Descriptive Statistics

CH2 also showed low communalities with other items, as did item CO2 of the Congruence scale. Because of these low communalities and their impact on scale reliability, we removed these items from the model. The remaining items loaded together on factors corresponding to our theoretical concepts.

Cronbach's alpha was calculated for each factor to assess internal reliability (Nunnally, 1978). All Cronbach's alphas were above 0.7 but for the Incentive scale; its two remaining items were slightly below 0.7, as shown in Appendix B. Keeping that information in mind, we proceeded with the rest of the analysis. The factor pattern matrix shown in Appendix C corresponds to the EFA without CH2 and CO2, which were removed in a previous step. For readability, as is common practice, Appendix C only shows loading coefficients above 0.3. The resulting matrix shows that all items load on expected constructs with loading coefficients above 0.5, demonstrating convergence validity (Fornell & Bookstein, 1982). The fact that items do not cross-load between factors shows discriminant validity. Discriminant validity is also supported by the factor correlation matrix shown in Appendix B. The matrix shows the square root of the average variance extracted (AVE) for each construct is greater than the correlations with other factors (Barclay et al., 1995). Heterotrait-Monotrait (HTMT) ratios are below 0.85 and also show discriminant validity (Kline, 2011).

We found no substantial evidence of common method bias. Harman's one-factor test shows that one factor explains only 26% of variance, well below the 50% regarded as detrimental (Podsakoff et al., 2003). No correlations between factors (Appendix B) are above 0.9 (Bagozzi et al., 1991). In the item correlation matrix provided by SPSS via the factor analysis, we looked at correlation coefficients that are significant at the 0.05 level (one-tailed chi-square test for ordinal Likert scale data). The second smallest statistically significant value is 0.113. When squared, it demonstrates that approximately 1.3% of the variance is due to a common-method bias variable, which is negligible (Lindell & Whitney, 2001; Malhotra et al., 2006).

In conclusion, the resulting factors of our EFA correspond to the expected constructs, and the measurement model is deemed to be reliable and valid enough to test our structural equation model.

5. ANALYSIS AND RESULTS

Before proceeding, we listed the levels our indicators of fitness needed to meet (Byrne, 2013; Hu & Bentler, 1999): the minimum discrepancy divided by degrees of freedom (PCMIN/DF) should be below 2. The comparative fit index (CFI) needs to be greater than 0.95. The Tucker Lewis Index (TLI) needs to be greater than 0.95. Further, based on Browne and Cudeck (1993), a root mean square error of approximation (RMSEA) below 0.05 shows a close fit. PCLOSE greater than 0.05 rejects the hypothesis that RMSEA is above 0.05, which confirms the close fit.

To test the structural equation model, we utilized the recommended two-step procedure by Anderson and Gerbing (1988). First, we tested the model fit with a confirmatory factor analysis (CFA). All indicators of fitness were very good: PCMIN/DF = 1.549, Comparative Fit Index (CFI) = 0.971, Tucker-Lewis Index (TLI) = 0.960, RMSEA = 0.047 with PCLOSE at 0.576.

Second, we tested the structural equation model. Fit was also good for this model (PCMIN/DF = 1.317, CFI = 0.982, TLI = 0.977, RMSEA = 0.036 with PCLOSE at 0.886). Figure 2 shows the results of the model tested. Standardized estimates and their p-values are displayed next to the paths. Percentages of the variable explained (R-squared) are displayed within the variables (27% of Satisfaction, and 9% of Incentive to Cheat). Table 3 provides a summary of the hypotheses testing results.

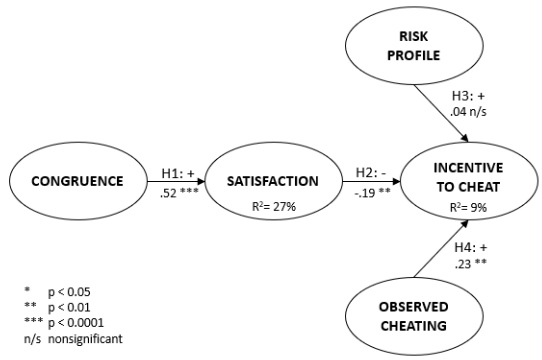


Figure 2. Structural Equation Model Testing Results

	Hypothesis	Result
H1	Perceived assessment congruence is positively related to satisfaction with the assessment tool.	Supported
H2	Satisfaction with the assessment tool is negatively related to incentive to cheat.	Supported
H3	Risk profile is positively related to incentive to cheat.	Not supported
H4	Observed cheating behavior is positively related to incentive to cheat.	Supported

Table 3. Support for the Hypotheses

6. DISCUSSION

For institutions attempting to reduce cheating in an academic setting, the results provide evidence that the incentive to cheat can be modified through the manipulation of at least three of the four factors identified, but perhaps the most important discussion topic is more practical in nature: focusing on how these items may lead to not only a decrease in academic dishonesty, but also an improved teaching environment with more reliable evaluation data.

6.1 Research Contribution

The model developed in this study is novel in the academic dishonesty research literature, in that it brings together aspects of multiple theories, focusing on factors that provide a student with the incentive to cheat: the individual's risk profile, satisfaction with the testing instrument, perceived assessment congruence, and the external influence of observed cheating. Each theory detailed in the literature has supporters, and each explains some aspect of why people do what they do, but a more unified theory incorporating aspects of each is a useful next step in this field of study. The model developed, and the results obtained, move in that direction.

Three of the four hypotheses were supported, with the strongest statistical evidence for H1; that perceived assessment congruence is positively related to satisfaction with the testing tool, supporting the findings of Kincaid and Zemke (2006). Our study also found support for H2; that satisfaction with the format reduces the incentive to cheat. The close relationship of congruence and satisfaction, and the clear evidence of the impact of these factors on the incentive to cheat, makes this an intriguing area for future research. As previously stated, Wenzel and Reinhard (2020) found that a student's negative perception of the measurement instrument will positively influence their desire to cheat. Our results support this assertion. The importance of perceived peer behavior, a long-standing staple of TRA and TPB, is confirmed in the specific case of cheating by this study. H4 received strong support; the incentive for a student to cheat is increased by the observed cheating of others. Cheating is, indeed, contagious (Rettinger and Kramer, 2009). Therefore, reducing cheating in one individual student should have the compounding value of reducing the incentive for others to cheat. Less observed cheating will lead to less incentive to cheat by others, which in turn leads to less observed cheating. This is a virtuous cycle that should be studied further and may provide a way to improve the performance of anti-cheating techniques. If students overestimate how many of their peers are cheating, it will help to make them aware of the reality of the situation. This may also provide support for honor codes and the recognition of ethical behavior, as suggested by Trevino and Nelson (2021).

The only hypothesis that did not receive support was H3. Our scale for Risk Profile loaded well, and the construct worked as expected. However, the construct had no impact on the other factors in the study, neither on Incentive to Cheat as theorized, nor Satisfaction, nor Congruence, as we tried other paths. On the one hand, we confirm that external influence matters (Observed Cheating), and perhaps acting on our identified internal process in the presence of external influence can only have limited impact. On the other hand, it shows that since external influence can never be alleviated, it is of importance to find other areas for action. Our study shows that we can work on perception associated with the test format to influence incentive to cheat.

Some of these academic contributions are of practical interest to researchers. First, we only had anecdotal evidence that students confuse being satisfied with the test format and finding the test format fair. Our study provides empirical support that this is the case. Although finding the test satisfying and fair are often considered two distinct concepts, the EFA showed that they loaded together. This is useful to know for future research. As researchers build their scales, they can potentially mix items that measure satisfaction with items that measure the perceived fairness of the assessment instrument. We recommend further research into the relationship between fairness and satisfaction, and the role of assessment congruence in these factors.

The second practical contribution pertains to the measurement of incentive to cheat. There is a debate among researchers regarding the inclusion of reverse items in surveys. Recent research confirms that reverse items can weaken empirical studies and offer guidelines to use them properly (Weijters & Baumgartner, 2012; Weijters et al., 2013). In these guidelines, they emphasize that some items cannot be reversed. In our study, CH2 measures if there is an incentive to cheat and the two other items measure if students felt there was no incentive to cheat. In the end, we recommend that researchers avoid mixing incentive and no-incentive items.

6.2 Instructional Contribution

Reducing the incentive to cheat helps to resolve the justifiable complaint that cheating is unethical and should be confronted, but there are other practical implications to this work that may be equally or more important. In particular, the results show that perceived assessment congruence and student satisfaction with the testing instrument are effective ways to reduce this unwanted practice. However, this also leads to a better evaluation process for the instructor. For a start, an exam that is more congruent with the material of the course will be a better instrument for measuring the students' knowledge of the course material. This is obvious, and should be the goal of all faculty, but an added bonus is the corresponding reduction of the incentive to cheat. This will also aid in the evaluation process, as instructors (and students) will receive more valid feedback from the tests, as opposed to data tainted by cheating behavior. In an era where cheating has been shown to be rampant, how confident can we be that our testing mechanisms are measuring actual student learning? A reduction in the incentive to cheat ensures that the test results data are more valid and, therefore, more useful to the instructor. In turn, this leads to a better learning experience for the students, as the assessment of learning (AOL) loop can be made complete, with faculty now able to better assess the students' understanding of the material and adjust class activities accordingly. In effect, this helps to remove the transactional focus of simply aiming for good grades by whatever means necessary, and hopefully places more of a focus on learning the material.

Secondly, instructors should know that fairness and satisfaction are entangled in students' minds. This should drive the way they design assessment tools and the communication around them. Ensuring that a testing format is seen as fair is a good way to ensure satisfaction. The study shows that one of the levers to ensure satisfaction is to ensure that the student perceives the format as testing the knowledge that was acquired in class.

6.3 Limitations and Future Research

We hope that this study provides a base for future research into this important topic. Some potential next steps have been outlined above, but perhaps the most useful next step would be to address the major limitation of this study: the lack of a measure of actual cheating behavior. There is ample research to imply that an incentive to cheat leads to the behavior, but it would be useful to expand the model to include behavior itself. A worthwhile first step could be a more TPB-based approach, inserting intent as the main predictor of behavior. Our focus on incentive theory as opposed to the TPB did not allow a comparison of incentive versus intent. We recommend that future studies measure each of these variables to allow for a comparison of the theories in the specific instance of cheating. The logical next step would be the inclusion of actual cheating behavior, although this is a very difficult construct to measure, due primarily to response bias in any questionnaires asking for self-reported information on behaviors seen as socially undesirable.

Similarly, this study limited the variables studied to those in the model presented in Figure 1. With Satisfaction and

Observed Cheating, our model only explains 9% of the variation in Incentive to Cheat. It is known, based on the literature cited earlier in the paper, that other factors such as unpreparedness, parents' pressure, and lack of teacher vigilance can potentially explain the incentive to cheat. We recommend an expanded model that could include such things as punishment severity and certainty from Deterrence Theory, factors from Expected Utility Theory, and perceived fairness as a precursor to satisfaction, based on the work of Wygal et al. (2017). The entanglement of fairness and satisfaction, as perceived by the students, is worthy of further investigation. We also did not utilize the rich stream of research in ethical decision-making. For example, Trevino and Nelson (2021) propose a decision-making process that begins with ethical awareness. They suggest that faculty should make their students aware of academic integrity policies, honor codes, etc., as a method to reduce unethical behavior. These ethical decision-making concepts are worthy of study. There are several other factors that can be identified from the literature, and a more comprehensive model may yield further strategies for combating the problem. This study was meant to provide a first step in this process. Finally, the addition of more data would also aid in the confirmation of our findings, as our study was limited to one specific information systems course with one specific assessment tool.

As for our measurement items, we confirm Weijters and Baumgartner's (2012) findings that reverse-scored items can cause issues. In our case, there may also be confusion in the wording of the items measuring incentive ("encourage" *vs.* "having an incentive"). The fact that the scale suffered from a lower than desired reliability (Cronbach's alpha slightly below 0.7, see Appendix B) also does not help with the percentage of variance explained. While we believe the students understood these to be the same concept, the effect found may have been greater if the measure was better worded.

Finally, as stated above, our study only involved the use of one MCQ exam. Some of the findings may not transpose easily to cases involving other types of assessment, such as essays or programming assignments. For example, we do not find support for students' Risk Profile impacting perceptions when we stay in the realm of MCQs, but it may be more essential in a situation where "gamblers" cannot choose a suggested answer but must generate it. The lack of significant relationship between Risk Profile and Incentive to Cheat might also come from the way concepts are measured in a survey. Risk Profile relates to the respondent's personal traits whereas Incentive to Cheat measures perceptions regarding "people" or "students" in general. Further, our scale is inspired by previous work using the DOSPERT scale (Blais & Weber, 2006; Coppola, 2014) but did not include their ethical items because students might have issues relating to them (these items are based on married life, having children, etc.). Some items also overlapped too much with the Incentive to Cheat variable we wanted to measure. This is a limitation because the predictive power of such a scale can vary depending on the items' domain (Coppola 2014). Therefore, we suggest that future researchers integrate personality traits such as Risk Profile into their studies and also measure models of cheating using a variety of assessment tools (e.g., other scales) embedded in not only surveys but experiments.

7. CONCLUSION

This paper provides evidence that the proposed predictive model of cheating incentive in students is valid and useful. Assessment congruence is found to be a precursor to satisfaction, which along with observed cheating is a precursor to the incentive to cheat. However, the student's risk profile was not found to have an impact. This has implications for academic institutions facing an epidemic of cheating on campus. Many institutions focus on increasing the risk of being caught and punished, but focusing on the student's satisfaction with the assessment process as a way of reducing the incentive to cheat is also key. Strategies need to be put in place to improve the students' satisfaction with the assessment tool. This may begin a virtuous cycle, where greater congruence between the class material and the assessment mechanism leads to greater satisfaction with the assessment, which leads to a reduction in the incentive to cheat. This, in turn, leads to more valid testing data for the instructor, which leads to even greater assessment congruence and satisfaction. The reduction in individual cheating will lead to a reduction in observed cheating, lowering the incentive to cheat even further. While reducing academic dishonesty is a good thing in and of itself, the potential improvement in learning is an excellent benefit.

While further research is recommended to determine other factors in the cheating decision, and perhaps using measures such as intent from TRA and TPB, we hope that this study provides a starting point for a more comprehensive response to cheating on college campuses.

8. REFERENCES

Ajzen, I. (1969). The Prediction of Behavior Intentions in a Choice Situation. *Journal of Experimental Psychology,* 5(4), 400-416. https://doi.org/10.1016/0022-1031(69)90033-X

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes,* 50(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1980). *Understanding Attitudes and Predicting Social Behavior*. Prentice-Hall.

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, 103(3), 411-423. https://doi.org/10.1037/0033-2909.103.3.411

Bagozzi, R.P., Yi, Y., & Phillips, L. W. (1991). Assessing Construct Validity in Organizational Research. *Administrative Science Quarterly*, 36(3), 421-458. https://doi.org/10.2307/2393203

Bain, L. Z. (2015). How Students Use Technology to Cheat and What Faculty Can Do About It. *Information Systems Education Journal*, 13(5), 92-99.

Ballantine, J. A., Guo, X., & Larres, P. (2018). Can Future Managers and Business Executives Be Influenced to Behave More Ethically in the Workplace? The Impact of Approaches to Learning on Business Students' Cheating Behavior. *Journal of Business Ethics*, 149(1), 245-258. https://doi.org/10.1007/s10551-016-3039-4

Barclay, D., Higgins, C., & Thompson, R. (1995). The Partial Least Squares (PLS) Approach to Causal Modeling:

Personal Computer Adoption and Use as an Illustration. *Technology Studies*, 2(2), 285-309.

Blais, A. R., & Weber, E. U. (2006). A Domain-Specific Risk-Taking (DOSPERT) Scale for Adult Populations. *Judgment and Decision Making*. 1(1), 33-47. https://doi.org/10.1017/S1930297500000334

Bretag, T., Harper, R., Burton, M., Ellis, C., Newton, P., van Haeringen, K., & Rozenberg, P. (2019). Contract Cheating and Assessment Design: Exploring the Relationship. *Assessment & Evaluation in Higher Education*, 44(5), 676-691. https://doi.org/10.1080/02602938.2018.1527892

Browne, M. W., & Cudeck, R. (1993). Alternative Ways of Assessing Model Fit. In K. A. Bollen & J. S. Long (Eds.), *Testing Structural Equation Models* (pp. 136-162). Newbury Park, CA: Sage.

Byrne, B. M. (2013). *Structural Equation Modeling With AMOS: Basic Concepts, Applications, and Programming*. Routledge. https://doi.org/10.4324/9781410600219

Chudzicka-Czupała, A., Grabowski, D., Mello, A. L., Kuntz, J., Zaharia, D. V., Hapon, N., Lupina-Wegener, A., & Börü, D. (2016). Application of the Theory of Planned Behavior in Academic Cheating Research–Cross-cultural Comparison. *Ethics & Behavior*, 26(8), 638-659. https://doi.org/10.1080/10508422.2015.1112745

Collignon, S.E., Chacko, J., & Wydick Martin, M. (2020). An Alternative Multiple-choice Question Format to Guide Feedback Using Student Self-Assessment of Knowledge. *Decision Sciences Journal of Innovative Education*, 18(3), 456-480. https://doi.org/10.1111/dsji.12213

Coppola, M. (2014). Eliciting Risk-Preferences in Socio-Economic Surveys: How Do Different Measures Perform? *The Journal of Socio-Economics*, 48, 1-10. https://doi.org/10.1016/j.socec.2013.08.010

D'Agostino, S. (2023, September 13). Why Professors Are Polarized on AI. *Inside Higher Ed*. https://www.insidehighered.com/news/tech-innovation/artificial-intelligence/2023/09/13/why-faculty-members-are-polarized-ai

Davis, S. F., Grover, C. A., Becker, A. H., & McGregor, L. N. (1992). Academic Dishonesty: Prevalence, Determinants, Techniques, and Punishments. *Teaching of Psychology,* 19(1), 16-20. https://doi.org/10.1207/s15328023top1901_3

Dey, S. (2021, August 27). Reports of Cheating at Colleges Soar During Pandemic. *NPR*. https://www.npr.org/2021/08/27/1031255390/reports-of-cheating-at-colleges-soar-during-the-pandemic

Ehrlich, I. (1996). Crime, Punishment, and the Market for Offenses. *Journal of Economic Perspectives*, 10(1), 43-67. https://doi.org/10.1257/jep.10.1.43

Fendler, R. J., Yates, M. C., & Godbey, J. M. (2018). Observing and Deterring Social Cheating on College Exams. *International Journal for the Scholarship of Teaching and Learning*, 12(1), article 4. https://doi.org/10.20429/ijsotl.2018.120104

Field, A. (2024). *Discovering Statistics Using IBM SPSS Statistics*. Sage Publications Limited.

Fishbein, M., & Ajzen, I. (1975). *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research.* Addison-Wesley.

Fornell, C., & Bookstein, F. L. (1982). Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory. *Journal of Marketing Research*, 19(4), 440-452. https://doi.org/10.1177/002224378201900406

Genereux, R. L., & McLeod, B. A. (1995). Circumstances Surrounding Cheating: A Questionnaire Study of College Students. *Research in Higher Education*, 36(6), 687-704. https://doi.org/10.1007/BF02208251

Gouldner A. W. (1960). The Norm of Reciprocity: A Preliminary Statement. *American Sociological Review*, 25(2), 161-178. https://doi.org/10.2307/2092623

Grecker, J., & Associated Press (Aug 10 2023). College Professors Are in 'Full-Blown Crisis Mode' as They Catch One 'ChatGPT Plagiarist' After Another. *Fortune*, https://fortune.com/2023/08/10/chatgpt-cheating-plagarism-college-professors-full-on-crisis-mode/

Houser, D., Vetter, S., & Winter, J. (2012). Fairness and Cheating. *European Economic Review*, 56(8), 1645-1655. https://doi.org/10.1016/j.euroecorev.2012.08.001

Hu, L., & Bentler, P. M. (1999). Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1-55. https://doi.org/10.1080/10705519909540118

Hughes, G. D. (2009). The Impact of Incorrect Responses to Reverse-Coded Survey Items. *Research in the Schools*, 16(2), 76-88.

Jones, B. D., & Egley, R. J. (2004). Voices From the Frontlines: Teachers' Perceptions of High-Stakes Testing. *Education Policy Analysis Archives*, 12(39), 1-34. https://doi.org/10.14507/epaa.v12n39.2004

Kaiser, H. F., & Rice, J. (1974). Little Jiffy, Mark IV. *Educational and Psychological Measurement*, 34(1), 111-117. https://doi.org/10.1177/001316447403400115

Kajackaite, A., & Gneezy, U. (2017). Incentives and Cheating. *Games and Economic Behavior*, 102, 433-444. https://doi.org/10.1016/j.geb.2017.01.015

Kincaid, C., & Zemke, D. M. V. (2006). Perceptions of Cheating: An Exploratory Study. *Journal of Hospitality & Tourism Education*, 18(1), 47-55. https://doi.org/10.1080/10963758.2006.10696849

King, C. G., Guyette, R. W., Jr., & Piotrowski, C. (2009). Online Exams and Cheating: An Empirical Analysis of Business Students' Views. *Journal of Educators Online*, 6(1), 1-11. https://doi.org/10.9743/JEO.2009.1.5

Klein, H. A., Levenburg, N. M., McKendall, M., & Mothersell, W. (2007). Cheating During the College Years: How Do Business School Students Compare? *Journal of Business Ethics*, 72(2), 197-206. https://doi.org/10.1007/s10551-006-9165-7

Kline, R. B. (2011) *Principles and Practice of Structural Equation Modeling*. Guilford Press.

Kohlberg, L. (1981). *The Philosophy of Moral Development: Moral Stages and the Idea of Justice*. Harper & Row.

Kremmer, M. L., Brimble, M., & Stevenson-Clarke, P. (2007). Investigating the Probability of Student Cheating: The Relevance of Student Characteristics, Assessment Items, Perceptions of Prevalence and History of Engagement. *International Journal for Educational Integrity*, 3(2), 3-17. https://doi.org/10.21913/IJEI.v3i2.162

Lang, J. (2013, September 11). News Flash… Harvard Students Cheat, Too. *Time*. http://ideas.time.com/2013/09/11/news-flash-harvard-students-cheat-too/

Lawson, R. A. (2004). Is Classroom Cheating Related to Business Students' Propensity to Cheat in the "Real World"? *Journal of Business Ethics*, 49(2), 189-199. https://doi.org/10.1023/B:BUSI.0000015784.34148.cb

Lindell, M. K., & Whitney, D. J. (2001). Accounting for Common Method Variance in Cross-Sectional Research Designs. *Journal of Applied Psychology*, 86(1), 114-121. https://doi.org/10.1037/0021-9010.86.1.114

Ling, C., & Libby, T. (2010). Writing Mini-Cases: An Active Learning Assignment. *Issues In Accounting Education*, 25(2), 245-265. https://doi.org/10.2308/iace.2010.25.2.245

Liu, Q., Wald, N., Daskon, C., & Harland, T. (2023). Multiple-Choice Questions (MCQs) for Higher-Order Cognition: Perspectives of University Teachers. *Innovations in Education and Teaching International*, 61(4), 802-814. https://doi.org/10.1080/14703297.2023.2222715

MacGregor, J., & Stuebs, M. (2012). To Cheat or Not to Cheat: Rationalizing Academic Impropriety. *Accounting Education*, 21(3), 265-287. https://doi.org/10.1080/09639284.2011.617174

Malhotra, N., Kim, S. S., & Patil, A. (2006). Common Method Variance in IS Research: A Comparison of Alternative Approaches and a Reanalysis of Past Research. *Management Science*, 52(12), 1865-1883. https://doi.org/10.1287/mnsc.1060.0597

McCabe, D. (2005). *Levels of Cheating and Plagiarism Remain High*. Center for Academic Integrity, Duke University.

McCabe, D. L., Butterfield, K. D., & Treviño, L. K. (2006). Academic Dishonesty in Graduate Business Programs: Prevalence, Causes, and Proposed Action. *Academy of Management Learning & Education*, 5(3), 294-305. https://doi.org/10.5465/amle.2006.22697018

McCabe, D. L., Treviño, L. K., & Butterfield, K. D. (2001). Cheating in Academic Institutions: A Decade of Research. *Ethics & Behavior*, 11(3), 219-232. https://doi.org/10.1207/S15327019EB1103_2

Morris, L. S., Grehl, M. M., Rutter, S. B., Mehta, M., & Westwater, M. L. (2022). On What Motivates Is: A Detailed Review of Intrinsic v. Extrinsic Motivation. *Psychological Medicine*, 52(10), 1801-1816. https://doi.org/10.1017/S0033291722001611

Murdock, T. B. (1999). Discouraging Cheating in Your Classroom. *Mathematics Teacher*, 92(7), 587-591. https://doi.org/10.5951/MT.92.7.0587

Newstead, S. E., Franklyn-Stokes, A., & Armstead, P. (1996). Individual Differences in Student Cheating. *Journal of Educational Psychology*, 88(2), 229-241. https://doi.org/10.1037/0022-0663.88.2.229

Nunnally, J. C. (1978). *Psychometric Theory* (2nd ed.), McGraw-Hill.

Oravec, J. A. (2023). Artificial Intelligence Implications for Academic Cheating: Expanding the Dimensions of Responsible Human-AI Collaboration With ChatGPT. *Journal of Interactive Learning Research*, 34(2), 213-237.

Owunwanne, D., Rustagi, N., & Dada, R. (2010). Students' Perceptions of Cheating and Plagiarism in Higher Institutions. *Journal of College Teaching & Learning*, 7(11), 59-68. https://doi.org/10.19030/tlc.v7i11.253

Passow, H. J., Mayhew, M. J., Finelli, C. J., Harding, T. S., & Carpenter, D. D. (2006). Factors Influencing Engineering Students' Decisions to Cheat by Type of Assessment. *Research in Higher Education*, 47(6), 643-684. https://doi.org/10.1007/s11162-006-9010-y

Peace, A. G., Galletta, D., & Thong, J. (2003). Software Piracy in the Workplace: A Model and Empirical Test. *Journal of Management Information Systems*, 20(1), 153-177. https://doi.org/10.1080/07421222.2003.11045759

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, 88(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Premeaux, S.R. (2005). Undergraduate Student Perceptions Regarding Cheating: Tier 1 Versus Tier 2 AACSB Accredited Business Schools. *Journal of Business Ethics*, 62(4), 407-418. https://doi.org/10.1007/s10551-005-2585-y

Rettinger, D. A., & Kramer, Y. (2009). Situational and Personal Causes of Student Cheating. *Research in Higher Education*, 50(3), 293-313. https://doi.org/10.1007/s11162-008-9116-5

Ritter, B. A. (2006). Can Business Ethics Be Trained? A Study of the Ethical Decision-Making Process in Business Students. *Journal of Business Ethics*, 68, 153-164. https://doi.org/10.1007/s10551-006-9062-0

Ryan, R. M., & Edward, L. D. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, 25(1), 54-67. https://doi.org/10.1006/ceps.1999.1020

Samuel, J., & Hinson, J. (2013). Are Your Students Cheating or Guessing on Tests? Consider Implementing Alternate Multiple-Test Formats Such as DOMC and NRET. *Society for Information Technology & Teacher Education International Conference* (pp. 4264-4269). Association for the Advancement of Computing in Education (AACE).

Schoemaker, P. J. (1982). The Expected Utility Model: Its Variants, Purposes, Evidence and Limitations. *Journal of Economic Literature*, 20(2), 529-563.

Shaw, M. (2022). Increased Use of Technology Facilitates Cheating. *The Southerner*. https://thesoutherneronline.com/86450/news/increased-use-of-technology-facilitates-cheating

Sims, R. L. (1993). The Relationship Between Academic Dishonesty and Unethical Business Practices. *Journal of Education for Business*, 68(4), 207-211. https://doi.org/10.1080/08832323.1993.10117614

Skinner, B. F. (1938). *The Behavior of Organisms*. Appleton-Century.

Smith, K. J., Emerson, D. J., & Mauldin, S. (2021). Online Cheating at the Intersection of the Dark Triad and Fraud Diamond. *Journal of Accounting Education*, 57, 100753. https://doi.org/10.1016/j.jaccedu.2021.100753

Smyth, M. L., & Davis, J. R. (2004). Perceptions of Dishonesty Among Two-Year College Students: Academic vs. Business Situations, *Journal of Business Ethics*, 51(1), 63-73. https://doi.org/10.1023/B:BUSI.0000032347.79241.3c

Tittle, C. R. (1980). *Sanctions and Social Deviance: The Question of Deterrence*. Praeger.

Toropin, K. (2021, August 20). At Least 100 Naval Academy Students Cheated on a Physics Test. 18 have been Expelled. *Military.com*. https://www.military.com/daily-

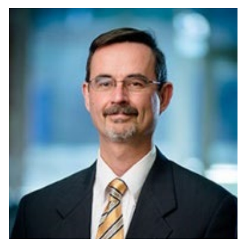
news/2021/08/20/least-100-naval-academy-students-cheated-physics-test-18-have-been-expelled.html
Trevino, L. K., Butterfield, K. D., & McCabe, D.L. (1998). The Ethical Context in Organizations: Influences on Employee Attitudes and Behaviors. *Business Ethics Quarterly*, 8(3), 447-476. https://doi.org/10.2307/3857431
Trevino, L. K., & Nelson, K. A. (2021). *Managing Business Ethics: Straight Talk About How to Do It Right (*8th ed.). Wiley.
Weijters, B., & Baumgartner, H. (2012). Misresponse to Reversed and Negated Items in Surveys: A Review. *Journal of Marketing Research*, 49(5), 737-747. https://doi.org/10.1509/jmr.11.0368
Weijters, B., Baumgartner, H., & Schillewaert, N. (2013). Reversed Item Bias: An Integrative Model. *Psychological Methods*, 18(3), 320-334. https://doi.org/10.1037/a0032121
Wenzel, K., & Reinhard, M. A. (2020). Tests and Academic Cheating: Do Learning Tasks Influence Cheating by Way of Negative Evaluations? *Social Psychology of Education*, 23(3), 721-753. https://doi.org/10.1007/s11218-020-09556-0
Whiting, H. J., Kline, T. J., & Sulsky, L. M. (2008). The Performance Appraisal Congruency Scale: An Assessment of Person-environment Fit. *International Journal of Productivity and Performance Management*, 57(3), 223-236. https://doi.org/10.1108/17410400810857239
Williams, M. R. (2020, October 12). 150 University of Missouri Students Caught Cheating on Exams Held Online Amid COVID-19. *The Kansas City Star*. https://www.kansascity.com/news/local/education/article246398985.html
Wygal, D. E., Stout, D. E., & Cunningham, B. M. (2017). Shining Additional Light on Effective Teaching Best Practices in Accounting: Self-Reflective Insights from Cook Prize Winners. *Issues In Accounting Education*, 32(3), 17-31. https://doi.org/10.2308/iace-51743

AUTHOR BIOGRAPHIES

Josey Chacko is an associate professor in the Richard J. Bolte Sr. School of Business at Mount St. Mary's University. Prior to earning his Ph.D. at Virginia Tech, he worked in manufacturing for close to 4 years. He is actively involved with the Information Systems for Crisis Response and Management (ISCRAM) group. Dr. Chacko's research has been published in various journals including *Decision Support Systems*.

Stéphane E. Collignon is an associate professor with the department of MIS at West Virginia University. He received his Ph.D. from Virginia Tech. Collignon's research interests are information systems issues in logistics, privacy management, and education. Collignon works with quantitative methodologies but is also an expert in qualitative research (Grounded Theory). He teaches information systems, data management, decisions sciences and business intelligence. Collignon worked for 7 years in R&D for two French distribution companies. His research notably appeared in *Information & Management*, *Journal of Business Logistics*, *European Journal of Operational Research*, and *Decision Sciences Journal of Innovative Education*.

Christina Green is an assistant professor of management in the Richard J. Bolte, Sr. School of Business at Mount St. Mary's University in Emmitsburg, MD. Prior to joining the Mount in 2016, Green worked in banking, fulfilling roles in consumer lending, branch management, securities and investments, and training and development. She most recently served as a community bank's talent development manager where she managed training initiatives, coached employees for development and performance improvement, and collaborated with executive management in strategic and succession planning. Green is also an organization development consultant, providing training in management and leadership.



A. Graham Peace is an associate professor of management information systems in the Chambers College of Business and Economics at West Virginia University. He formerly worked at IBM, and obtained his doctorate from the University of Pittsburgh. Dr. Peace has served as Associate Dean for Undergraduate Programs and Chair of multiple departments while at WVU. His research and teaching interests include information ethics, database management systems, and pedagogical issues.

https://doi.org/10.62273/CSGL6637

APPENDICES

Appendix A. Exam Format and Survey Questionnaire

For our second mid-term exam, we used the test format validated by Collignon et al. (2020). This format was presented in class before the exam date and was then explained again just before the exam took place. The format follows a regular MCQ format in which you circle the answer you think is correct, but an extra option of "I don't know" is offered for a 0.35-point reward. Using this format was justified by the gain in information afforded (Collignon et al. 2020), which allows the instructor to return better targeted feedback.

In the questionnaire, the students were prompted as follows: Keeping in mind the new type of multiple-choice test in which you can circle one answer or opt for the 0.35pt option (Mid-Term II type), please indicate your extent of agreement to the following statements on the scale shown below: [Likert scale from 1 to 5, strongly disagree to strongly agree].

The questionnaire and descriptive statistics are shown in Table A-1.

Construct	Item	Text	Mean	Std Dev
Satisfaction	OS1	I think this format of testing is a satisfactory way to test people	3.48	0.818
	OS2	I like this type of test for assessing students	3.17	0.954
	FA1	I think this type of test is fair	3.63	0.833
	FA2	I believe this way of testing students is fair	3.58	0.834
	FA3	In my opinion, this format of test is a fair way of evaluating students	3.47	0.871
Congruence	CO1	I think this format of test rewards people who know the answers to the questions.	3.51	1.035
	CO2	I think only students who know the class material perform well with this type of test.	3.38	0.949
	CO3	In my opinion, people who truly know the answer are better rewarded with this format of test.	3.33	1.076
Risk Profile	RP1	I perceive myself as a risk taker.	3.21	0.984
	RP2	In games of chance I play for high stakes.	3.07	1.038
	RP3	In general, if I were to invest I would prefer to invest in stock with minimal risk and I am willing to accept the associated lower return (reverse coded).	2.85	0.964
Incentive to Cheat	CH1	I think a student has no incentive for cheating with this format of testing (reverse coded).	3.20	0.952
	CH2	In my mind, people are encouraged to cheat with this type of test.	2.18	0.810
	CH3	I believe that people are not influenced towards cheating with this type of test (reverse coded).	2.95	0.857
Observed Cheating	CH4	Other people have told you that they saw students cheating on Midterm II.	1.56	0.780
	CH5	I personally have seen students cheating on Midterm II.	1.51	0.750

Table A-1. Questionnaire and Descriptive Statistics

Appendix B. Validity and Reliability Indicators

	Indicators		Factor Correlation Matrix (PAF), Square root of AVE on diagonal				
Factor	**Cronbach's Alpha**	**AVE (PCA*)**	**Satis**	**Risk Profile**	**Obs. Cheat.**	**Cong.**	**Incent.**
Satisfaction	.887	.686	**.783**				
Risk Profile	.778	.694	.074	**.754**			
Obs. Cheat.	.797	.832	-.153	-.023	**.817**		
Congruence	.740	.774	.478	.123	.002	**.762**	
Incentive	.631	.724	-.152	.038	.244	-.203	**.704**

** The EFA was performed with two methods of extraction in SPSS, principal component analysis (PCA), and principal axis factoring (PAF). Results are similar with both methods.*

Appendix C. Pattern Cross Loading Matrix

	Factor				
	1	2	3	4	5
OS1	**0.729**	0.030	0.025	0.077	-0.054
OS2	**0.819**	-0.081	0.018	-0.126	0.016
FA1	**0.749**	0.034	0.017	0.045	-0.037
FA2	**0.828**	-0.024	-0.025	-0.013	-0.003
FA3	**0.784**	0.043	-0.057	0.060	0.080
CO1	0.023	-0.012	-0.010	**0.748**	-0.061
CO3	0.009	0.012	0.023	**0.776**	0.072
CH1(rev)	-0.091	-0.014	-0.064	0.033	**0.824**
CH3(rev)	0.125	-0.018	0.102	-0.038	**0.560**
CH4	-0.052	0.034	**0.813**	0.013	0.044
CH5	0.033	-0.034	**0.821**	-0.001	-0.034
RP1	0.016	**0.758**	0.032	-0.003	0.015
RP2	0.018	**0.901**	-0.008	-0.061	0.037
RP3(rev)	-0.048	**0.564**	-0.027	0.069	-0.088

This matrix is extracted with Principal Axis Factoring, rotation with Promax with Kaiser Normalization.

INFORMATION SYSTEMS & COMPUTING ACADEMIC PROFESSIONALS

iscap

STATEMENT OF PEER REVIEW INTEGRITY

All papers published in the ***Journal of Information Systems Education*** have undergone rigorous peer review. This includes an initial editor screening and double-blind refereeing by three or more expert referees.

ISSN: 2574-3872 (Online) 1055-3096 (Print)