Fraud prevention software and its impact on decision making

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Abstract

This study investigates the influence of using an automated decision-aid system to identify potential fraud perpetrators and the framing of the report on the intention to initiate a fraud investigation. Results from the experiment indicate that the use of automated decision-aid systems interact with the framing of the information. People are more likely to initiate a fraud investigation when the report is generated by an automated decision-aid system that discloses the probability of correctly identifying a potential fraud perpetrator than when the report is generated by a manual decision-aid system. However, when the report discloses the probability of incorrectly identifying a potential fraud perpetrator no difference on the intention to initiate an investigation (between manual and automated systems) is observed. Overall the results indicate that the influence of using automated decision aids depends on the framing of the information.

Keywords: Fraud prevention software, framing, cognitive bias

Introduction

Fraud is a growing concern among business leaders and regulators, with a steady increase reported in the number and magnitude of cases (ACFE 2008). Employee fraud cost companies $994 billion in losses in 2008 (ACFE 2008), compelling the development of more effective methods to prevent fraud. Technology has been instrumental in this effort by automating systems for the continuous monitoring of information. This research investigates whether the use of automated decision-aid systems to identify employees who fit the profile of fraud perpetrators affect the decision to investigate suspected fraud. We investigate also whether the framing of the report influences this decision.

Decision-aid software has been recently used for fraud prevention. One example is a program that identifies disgruntled employees by data mining email messages—disgruntled employees may be an early indicator of potential fraud (Holton 2009). In addition to the ability to analyze a large amount of data, automated decision aids have also been developed to overcome biases in decision making (Rose 2002). However, it is unclear whether reliance on software exacerbates or mitigates cognitive biases such as the framing effect. Therefore, we conduct an experiment to investigate the influence of using automated decision-aid systems and the framing of the report, on decision making.

We are interested in the intention to initiate a fraud investigation depending on the framing of the report. The way the information reported is framed can cause managers to undertake costly and unnecessary investigations. On the other hand, framing can also cause managers to disregard necessary investigations. Failing to launch a timely fraud investigation defeats the purpose of preventive mechanisms to deter fraud.

This paper is organized as follows. First, we review the literature of cognitive limitations and software reliance. Then, we explain the experimental procedure in the research method section. Next, we present the results of the data analysis and discuss the results. Finally, we draw conclusions from the study and discuss its limitations and potential areas for future research.

Literature review and hypotheses development

Decisions are influenced by a person's limited information processing capabilities; these limited capabilities are known as cognitive limitations (Simon 1957). Researchers and practitioners are interested in understanding cognitive limitations because they cause people to make suboptimal decisions (Simon et al. 1987). A clear understanding of the factors that mitigate or exacerbate cognitive limitations is important to identify solutions to overcome them. Research on cognitive limitations is extensive in the accounting literature (Hogarth 1991, 1993). However, the literature has mainly focused on auditing (Hogarth 1991), with limited research on accounting information systems in general, and automated decision-aid systems in particular (Rose 2002).

Automated decision-aid systems aim to help users overcome cognitive limitations (Todd and Benbasat 2000); nevertheless, these systems sometimes fail in their goal as they can "create biases and intensify shortcomings in human information processing" (Rose 2002, 116). One bias that might result from processing information is framing, which refers to the bias created by the way the information is presented or framed. Prospect theory, proposed by Tversky and Kahneman (1981), explains the framing bias by arguing that people are loss averse; for rationally equivalent choices, people prefer choices stated as gains rather than choices stated as losses. That is, when an individual has two options that are rationally equivalent choices, there should be no difference which option is preferred, yet people typically prefer choices that are stated as gains. Similarly, when people are presented with two equivalent loss situations, people tend to act upon the option that highlights the loss in an effort to minimize it. That is, highlighting the loss makes people more aware of the potential loss and incentivizes them to act to reduce the loss.

We select the framing bias for the following three reasons. First, although there is extensive research on the impact of framing in multiple contexts, there is no evidence of the moderating effect of the use of automated decision-aids on framing. Framing might be alleviated or exacerbated by the tendency of people to rely on software for decision making.

Second, as automated decision aids move from deterministic to non-deterministic tasks the reports derived from these systems are more likely to include information about the probability of correctly identifying or solving the issues at hand. These probabilities can be expressed in different ways which might influence decision making. For instance, ninety percent of the probability of correctly identifying a problem or ten percent of the probability of incorrectly identifying a problem is rationally equivalent, but the framing of the statement can influence the decision to be made.

Third, when using automated decision-aid systems users base their decisions, among other factors, on the reports generated by the decision-aid. People can either actively use automated decision-aids along different stages of the decision making process or they can be passive users of decision-aid software where they are only provided with a final outcome. Therefore, the framing of the report influences any type of user, either passive or active.

Biases from interacting with automated or manual decision-aid systems can arise in every stage of the decision making process. Data might be input incorrectly, interaction during the processing might be deficient, and output reports might be misinterpreted. To isolate the framing effect we focus only on the report generated by the system. Therefore, based on prospect theory, we seek to confirm the expected framing bias as expressed in our first hypothesis:

H1: Participants presented with a report that highlights the loss are more likely to initiate a fraud investigation (loss aversion) than participants presented with a report that does not highlight the loss.

In the current study, we focus on automated decision-aid systems to identify potential fraud perpetrators. Automated systems to support fraud prevention and detection are increasingly used (ACFE 2008). One type of software allows for data mining email messages to identify disgruntled employees, which may be an early indicator of potential fraud (Holton 2009). The practice of data mining employees' emails has increased because email communications can be used to demonstrate misconduct, such as in the Enron case (Hunter 2007). Email communications are an abundant source of data that can be used not only for ex-post evidence, but can also be used ex-ante to identify discontented employees, allowing companies to launch focused investigations to prevent fraud (Pemble 2003a; Pemble 2003b).

Using automated decision-aid systems is a double-edged sword, however; they can increase the effectiveness and efficiency of the decisions made when used appropriately but they can also decrease the effectiveness and efficiency of the decisions when used inappropriately. The suitable use of a decision aid rests on the actual acceptance and consideration of the information reported by the system, known as reliance. Both over-reliance–undue reliance on the decision aid–and under-reliance–disregarding the decision aid–can be detrimental for decisions.

Arnold and Sutton (1998) propose the theory of technology dominance to help understand the influence of automated decision aids on decision makers' judgments. The theory identifies four factors influencing users' reliance on automated decision aids: task experience, task complexity, decision aid familiarity, and cognitive fit. Appropriate reliance on the decision aid can only occur when these factors are aligned (adequate task experience, adequate task complexity, adequate decision aid familiarity, and adequate cognitive fit).

Arnold, Collier, Leech, and Sutton (2004) test the theory of technology dominance using an automated decision aid to support solvency decision problems. They manipulate the order in which the information is presented. The order of presentation is a cognitive bias known as order-effect, which causes people to perceive information presented recently as more relevant than information presented earlier. The authors find that the automated decision aid exacerbates the order-effect bias of inexperienced users while partially alleviating the bias of experienced users.

Hampton (2005) tests the overall model of the theory of technology dominance and finds support for three of the four factors influencing reliance (task experience, task complexity, and cognitive fit). Familiarity with the decision aid does not influence user reliance. Experience is negatively related to reliance; inexperienced users rely more on automated decision aids than experienced users regardless of the task complexity and cognitive fit.

In summary, the literature suggests that the use of automated decision-aids systems can exacerbate cognitive biases when users over-rely on the decision aid. However, these studies investigate automated decision aids without comparing the outcome from using manual decision aids. For instance, inexperienced users may be more susceptible to order-effect bias than experienced users regardless of the use of automated decision aids. Without comparing the decision aid results with a manual process, we cannot say for certain that using the aid is really exacerbating the bias.

We argue that to determine if automated decision aids indeed exacerbate or ameliorate cognitive biases a benchmark is needed to assess the presence of the cognitive bias in the absence of the automated decision aid. A manual decision aid system performing the same task can be used as a benchmark: if users behave differently when relying on an automated decision aid system, as opposed to a manual decision aid system, then we can be certain that this difference is caused by the reliance on the automated decision aid. Based on the theory of technology dominance we propose the following hypothesis.

H2 Participants presented with a report generated by an automated decision-aid system are more likely to initiate a fraud investigation than participants presented with a report generated by a manual decision-aid system.

Relying on automated decision aids might interact with the framing of information. It is possible that people's desire to avoid losses will be greater when relying on the information provided by automated decision aids than when relying on the information provided by manual systems. In the absence of theory predicting the interaction of framing and the use of automated decision-aid systems, we propose an exploratory hypothesis indicating the possibility of such interaction without stating the direction expected.

H3 The framing bias is moderated by the information generated by an automated decision-aid system.

The following section discusses the research method we use to test the hypotheses.

Research method

We conduct an experiment to understand the influence of automated decision-aid systems and framing on the decision to initiate a fraud investigation. The automated decision-aid system is manipulated at two levels: no automated decision-aid system (i.e., manual decision-aid system) and automated decision-aid system. Framing is also manipulated at two levels:

information highlighting a loss and information that does not highlight a loss. In short, we conduct a full factorial 2X2 between subjects experimental design.

We use a vignette approach, providing participants a business scenario that instructs participants to assume they are managers for a company using a decision-aid system to identify the profile of potential fraud perpetrators. After reading the scenario they are informed that the report generated by the decision-aid system (manipulated as manual or automated) has identified a certain employee as fitting the profile of a disgruntled employee and as such is considered a potential fraud perpetrator.

To manipulate framing we present participants with one of two possible loss situations. The scenario discloses that there is a probability that the system has correctly (or incorrectly) identified the employee as disgruntled. Both probabilities are rationally equivalent: 80 percent probability of correctly identifying a disgruntled employee or 20 percent probability of incorrectly identifying an employee as disgruntled. The 80 percent probability of correctly identifying a disgruntled employee confirms the status quo; that is, it confirms that the decision-aid system works as expected. The 20 percent probability of incorrectly identifying an employee as disgruntled highlights the loss situation because it emphasizes the possibility of making a mistake. According to prospect theory, we expect participants presented with information framed as 20 percent probability of incorrectly identifying an employee as disgruntled to be more likely to initiate a fraud investigation.

The dependent variable—intention to initiate a fraud investigation—is measured by a composite variable including six items using a 7-point Likert scale (strongly disagree-strongly agree) similar to the items commonly used to measure behavioral intention (Ajzen and Fishbein 1980). Because the study focuses on the influence of automated decision-aid systems, the individuals' tendency to rely on software can affect their decision. Therefore, to control for this effect we adapt a reliance measure developed by Hampton (2005) to measure an individual's reliance on automated and manual systems. We measure reliance on manual and automated systems with four items each using a 7-point Likert scale (strongly disagree-strongly agree).

We include two additional measures of trust in automation as control variables, because trust has been identified as an antecedent of reliance (Lee and See 2004). Trust on a decision aid is dynamic and depends on multiple factors including the reliability and validity of the decision-aid. In our experiment, participants do not actually interact with the system but make decisions based on the report generated by the system. Therefore, rather than asking participants about their trust on a specific decision-aid system we ask about their trust on decision-aid systems in general. The factors that influence the preliminary trust in the system are those that exist at the initial stage of trust: perceived reputation and trusting intentions (Li et al. 2008). We measure perceived reputation and trusting intentions for manual and automated systems with three items for each measure using a 7-point Likert scale (strongly disagree-strongly agree) adapted from Li et al (2008). All control variables are asked before presenting the vignette to avoid biasing participants' responses.

The instrument also includes general demographic information. In addition to asking participants for general working experience, we ask about experience in fraud investigations to identify whether they have experience in the domain specific task. The English version of the vignette and the constructs are presented in the Appendix. The original instrument was developed in English because the validated scales used are in English. We translated the instrument to Spanish because the participants were drawn from a Spanish speaking population. As customary in cross-cultural research, the instrument was translated to Spanish and backtranslated to English by independent translators. The instrument was then adjusted to ensure a valid translation. We also conducted a pilot study to identify potential problems with the instrument.

Results and discussion

Participants are graduate business students from a Mexican university. We consider graduate students a suitable population because they are part-time students with professional experience. The fact that they might not have experience in fraud investigation favors our study because inexperienced users are more likely to rely on automated decision-aid systems; if decision-aid software exacerbates or ameliorates the framing effect in inexperienced users then we are more likely to find a significant effect on data collected from this sample. Permission was granted by instructors of various courses for one of the researchers to conduct the experiment during regular class time. Participation was anonymous and voluntary and no incentives were given to participate. Participants were randomly assigned to one of the four experimental conditions.

Our sample comprises 53 participants, 20 (38%) are women and 33 (62%) are male. The mean (standard deviation) age and working experience is 39 (9) and 13 (8) years respectively. Three participants indicated that they had working experience on fraud investigation (5, 10, and 12 years). We conducted our data analysis including and excluding the three participants with experience in fraud investigations and the results remained the same. We report the results including these three participants.

We first test the validity and reliability of the constructs by performing a factor analysis (principal components and varimax rotation) and calculate Cronbach alphas. For the control variables, the factor analysis indicates that all items clearly loaded on the intended construct. The lowest Cronbach alpha observed is .8, beyond the .7 recommended (Nunnally and Bernstein 1994). To create an overall construct for each concept (reliance, perceived reputation, and trusting intention) we deduct the participants' responses for manual systems from the responses for automated systems. We then calculate the mean for the items in each construct to create a composite variable.

For the dependent variable (likelihood to initiate a fraud investigation) the factor analysis finds two factors, with four items clearly loading on the first factor, one item loading on the second factor, and one item cross-loading on both factors. We eliminate the two factors that do not exhibit adequate loading. As a consequence, the Cronbach alpha increases from an original .74 when the six items are included to .84 when only four items are included. We decide to conduct the analysis with the construct including only the four items that exhibit adequate loadings. Table 1 presents the descriptive statistics for the dependent variable in each of the experimental conditions.

Table 1 Descriptive statistics for experimental conditions

		Decision-aid system	
		Manual	Automated
Frame	Correct information	4.44 (1.37) 12	5.70 (1.18) 10
	Incorrect information	5.10 (1.40) 18	4.98 (1.51) 13

Mean (standard deviation) number of cases

We use ANOVA to assess the impact of the experimental conditions on the intention to initiate a fraud investigation. The model includes two main effects, an interaction, and three control variables. The result from the analysis is presented in Table 2.

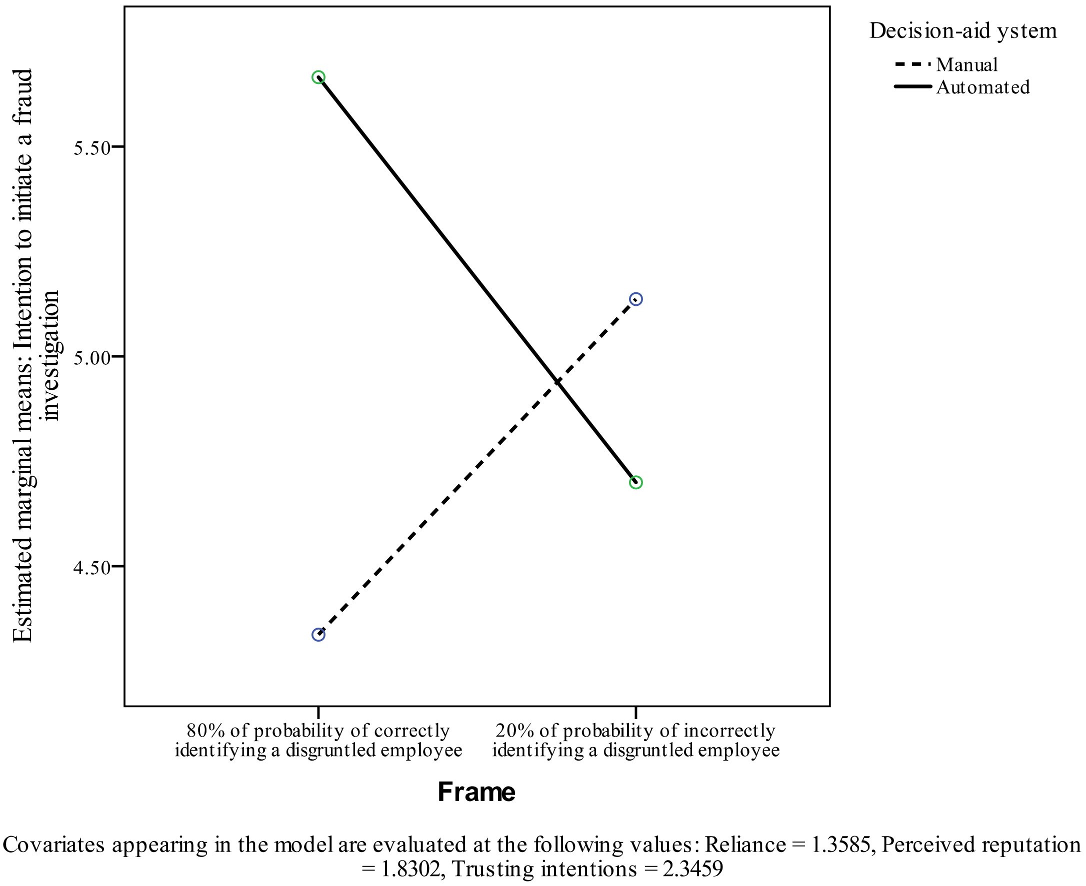
Table2 Hypotheses test: Effects of automated decision-aid system and framing on the intention to initiate a fraud investigation

	Sum of Squares	Degrees of freedom	Mean Square	F	Sig.
Corrected Model	23.604	6	3.934	1.896	.102
Intercept	327.961	1	327.961	158.069	.000
Reliance	3.087	1	3.087	1.488	.229
Perceived reputation	1.296	1	1.296	.625	.433
Trusting intentions	2.056	1	2.056	.991	.325
Framing (H1)	.083	1	.083	.040	.843
Decision-aid system (H2)	2.497	1	2.497	1.203	.278
Decision-aid system * Framing (H3)	9.357	1	9.357	4.510	.039
Error	95.441	46	2.075		
Total	1416.688	53			
Corrected Total	119.045	52			

R Squared = .198 (Adjusted R Squared = .094)

The main effects for hypothesis 1 and 2 are not significant (p=.843 and p=.278 respectively), however the interaction is highly significant (p=.039). In the presence of significant interactions interpreting main effects is misleading because they present a partial view of the total effect (Gamst et al. 2008). Following Gamst el al. (2008), we interpret the interaction testing the different effects with post-hoc comparisons adjusting for experiment-wise errors to maintain the alpha level at .05. Pair-wise post-hoc analysis is conducted using Bonferroni procedures, which is a conservative procedure to adjust alpha levels (Gamst et al. 2008). Figure 1 displays the interaction between the use of automated decision-aid systems and framing.

Figure 1 Interaction of decision-aid system and framing



When information is framed as 80% probability of the system correctly identifying a disgruntled employee, participants who were told the report was generated by an automated decision-aid system are more likely to initiate a fraud investigation than those who were told the report was generated by a manual decision-aid system (p=.038). However, when the information is framed as 20% probability of the system incorrectly identifying an employee as disgruntled, the intention to initiate a fraud investigation is not statistically different for either type of system (manual or automated) (p=.42).

The p-values for pair-wise comparisons of the framing effect on automated and manual decision-aid systems are .13 and .14 respectively. These results are not significant at conventional alpha levels of .05. We consider this to be the result of the small sample size; significant results might be obtained with a larger sample increasing the power of the analysis.

Conclusions, limitations, and areas for future research

As expected, participants in the manual system condition were more likely to launch an investigation when they read reports framed as 20% probability of incorrectly identifying an employee as disgruntled (loss aversion). Participants in the automated decision-aid condition, however, relied on the reports generated from the system and were more likely to initiate a fraud investigation when the report was framed as 80% probability of correctly identifying a disgruntled employee. We find, therefore, that the influence on framing bias generated by the use of automated decision-aid systems is not straightforward. The framing bias is exacerbated when the information confirms the expected behavior of the system possibly because people over-rely on the system. However, when the information discloses the probability that the system has performed a task incorrectly the use of automated decision-aid systems does not influence the framing bias and people behave as they would behave using a manual decision-aid system. The lack of a unique effect of the use of automated decision aid systems points to the need to develop theory that can explain the circumstances under which automated decision-aid systems exacerbate or ameliorate biases.

Culture may influence reliance on software (Lee and See 2004). Findings from the current study conducted in Mexico may not be generalizable to other populations. For future research, it would be interesting to compare results from other countries with different cultural characteristics.

Prior research has found that automated decision-aid systems influence decision making by inexperienced users (Arnold et al. 2004). Although the current study investigated only inexperienced participants, an interesting extension could include participants with experience in fraud investigation to contrast the influence of automated decision aids and framing from experienced and inexperienced users.

Appendix

Vignette

Experts in fraud investigations have identified three factors that are present when fraud is committed: opportunity, rationalization, and motive. Opportunity refers to a lack of oversight, such as weak internal controls, which allows a person to commit fraud. Rationalization refers to the mindset of the person justifying the fraud. Motive refers to the person's need (monetary or psychological) to commit the fraud.

Rather than investigating fraud after the fact, it would be more constructive for managers to focus on fraud prevention. One characteristic of interest is identification of disgruntled or unhappy employees. Unhappy employees are more likely to commit fraud because they rationalize fraud in terms of getting even with the organization. For instance, employees unhappy with their salaries might rationalize that fraud is a way of receiving compensation for being underpaid.

FACTS:

Assume that you are a manager for a company. An auditor from (Software used in) the internal audit department identifies disgruntled or unhappy employees by analyzing employees' email. Each month, the auditor (software) browses through that month's emails, searching for communications that might indicate unhappiness or the desire to get even with the company.

Every month the internal auditor (software) prepares (generates) a report that identifies employees as fitting the profile of a disgruntled worker. Based on the report you need to decide whether a deeper investigation should be launched. You know that the interpretation of emails is contextual; therefore, there is the possibility of incorrectly identifying a disgruntled employee (that is, the employee is identified as unhappy when in fact he/she is not). Also there is the possibility of failing to identify a disgruntled employee (that is, a disgruntled employee is not identified).

This month the internal auditor (the software) informs you (reports) that a certain employee, Smith, fits the profile of a disgruntled employee. There is an 80% probability (20%) that Smith has been correctly (incorrectly) identified as a disgruntled employee.

Dependent variable – behavioral intention (intention to initiate a fraud investigation) – Adapted from Ajzen and Fishbein (1980).

1. I would request that emails from previous month for Smith be analyzed.
2. I would do nothing.
3. I would wait until the next month's report to verify if Smith is again identified as a disgruntled worker.
4. It is extremely likely that I would request an analysis of emails written by Smith.
5. My commitment to additional analysis of emails written by Smith is extremely strong.
6. I am extremely certain that I will conduct an investigation of Smith.

Control variables

Reliance – Adapted from Hampton (2005).

1. Information reported by automated systems is accurate.
2. I feel confident about information reported by automated systems.
3. I would use information reported by automated systems to make a decision.
4. I would rely on the information reported by automated systems when forming a decision.
5. Information reported by manual systems is accurate.
6. I feel confident about information reported by manual systems.
7. I would use information reported by manual systems to make a decision.
8. I would rely on information reported by manual systems when forming a decision.

Perceived reputation – Adapted from Li et al. (2008).

1. Automated systems are known for working for the best interest of employees.
2. Automated systems have a reputation for being competent.
3. Automated systems are recognized for being reliable.
4. Manual systems are known for working for the best interest employees'.
5. Manual systems have a reputation for being competent.
6. Manual systems are recognized for being reliable.

Trusting intention - Adapted from Li et al. (2008)

1. I would feel comfortable depending on an automated system.
2. I would feel comfortable supporting the adoption of an automated system.
3. I would feel comfortable using an automated system.
4. I would feel comfortable depending on a manual system.
5. I would feel comfortable supporting the adoption of a manual system.
6. I would feel comfortable using a manual system.

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