Investigating the Effect of Insurance Fraud on Mouse Usage in Human-Computer Interactions

Completed Research Paper

Martin Hibbeln
Braunschweig Institute of Technology
Braunschweig, Germany
martin.hibbeln@tu-bs.de

Jeffrey L. Jenkins
Brigham Young University
Provo, Utah
jjenkins@byu.edu

Christoph Schneider
City University of Hong Kong
Hong Kong, China
christoph.schneider@cityu.edu.hk

Joseph S. Valacich
University of Arizona
Tucson, Arizona
valacich@email.arizona.edu

Markus Weinmann
University of Liechtenstein
Vaduz, Liechtenstein
markus.weinmann@uni.li

**Authors Listed Alphabetically*

Abstract

The completion of online forms is the catalyst for many business and governmental processes. However, providing fraudulent information in such forms is pervasive, resulting in costly consequences for organizations and society. Furthermore, detecting fraudulent responses in online forms is often very difficult, time consuming, and expensive. This research proposes that analyzing users' mouse movements may reveal when a person is being fraudulent. Namely, based on neuroscience and deception theory, the paper explains how deception may influence hand movements captured via the computer mouse. In an insurance fraud context, a study is conducted to explore these proposed relationships. The results suggest that being deceptive may increase the normalized distance of movement, decrease the speed of movement, increase the response time, and result in more left clicks. Implications for human-computer interaction research and practice are discussed.

Keywords: Human-computer interaction, Fraud, Mouse Movements

Introduction

The completion of online forms is the catalyst for many business and governmental processes. However, providing fraudulent information in such forms (e.g., online job applications, insurance claims, visa applications, etc.) is pervasive in society. For instance, insurance claim fraud (increasingly filled out using online forms) is the second largest white collar crime in the United States after tax evasion (Dean 2004), resulting in damages from US$80 to US$120 billion per year (Coalition Against Insurance Fraud;

Coolidge 2006; Smith 2000). In Quebec, Canada, more than 10% of all car insurance claims were found to be fraudulent (Caron and Dionne 1999). The Inspector General for Tax Administration in the US Treasury Department reported that fraudulent tax refunds (also increasingly filled out online) exceeded US$3.6 billion in 2011 (Barnes 2013). With the advent of the Affordable Care Act in the US, experts further predict massive increases in tax fraud (Dorfman 2013). While often considered a “victimless crime” (e.g., Morley et al. 2006), fraudulent claims cause tremendous costs for organizations, governments and society.

Despite the deleterious impacts of fraud, identifying and taking action to mitigate its impacts is challenging. With millions of claim documents to process and understand, by both businesses and governmental agencies, along with fraudulent claims ranging from slight misrepresentations to fully fraudulent claims, auditors have long focused on the easy to identify and most egregious instances. Traditional methods for identifying fraud can range from automated ratio analysis to human-based investigations that can be expensive and slow. Due to the costs, both time and money, associated with identifying fraudulent claims, it has not been practical to verify all claims. Likewise, delaying claim processing for honest customers until some type of analysis is completed can lead to customer dissatisfaction and have reputational costs for the insurer (Picard 1996). Therefore, improved approaches for identifying fraudulent claims will have positive downstream impacts on consumers and society.

One potential efficient and mass-deployable method for detecting fraud is through monitoring people’s mouse cursor movements (Valacich et al. 2013). The analysis of mouse movements has been suggested to reveal hidden psychological states that are not availed by traditional measures (Freeman et al. 2011), including emotional arousal and valence (e.g., Grimes et al. 2013b), cognitive conflict (e.g,. Dale et al. 2007), and increased cognitive processing (Freeman and Ambady 2011). In a human-computer interaction context, research has proposed that deception can cause uncontrollable, yet measurable, changes in people’s keystroke dynamics (how one types on the computer keyboard) (Grimes et al. 2013a). Although past research has suggested that mouse movements may also be influenced by deception (e.g., Valacich et al. 2013), limited research has theoretically developed and empirically validated hypotheses on how deception influences mouse movements.

Drawing on psychological and neuroscience theory, this paper explains and empirically validates how deception in online forms influences people’s hand movements, and thereby mouse cursor movements. In doing so, this paper answers the following research question: How does fraud in online forms influence mouse cursor movements? To answer this research question within a context, this paper focuses specifically on fraudulent insurance claims that are completed online—i.e., claims filed by customers to report damages to insurance companies for reimbursement. Hypotheses are developed and empirically tested using a mock insurance claim processing study. The results of the study indicate that being fraudulent while filling out online insurance claim forms is correlated with increases in the normalized mouse cursor movement distance (distance that occurs in addition to the required distance to complete one’s action), decreases in movement speed, increases in response time, and increases in the number of left clicks.

Brief Literature Review

Insurance fraud is a widespread type of fraud in online forms. Fraudulent insurance claims cause tremendous monetary losses for insurance companies, resulting in increased premiums for other policyholders. Fraudulent behavior includes falsification of details to qualify for cover, claims for losses that have never really occurred, as well as exaggerated claims or “build-ups” (Clarke 1990). One common form of fraud is exaggerating damages to reclaim one’s deductible. Deductibles are often perceived as being unfair, and can thus increase the likelihood of fraudulent behavior because the insured may lie about the amount of loss to recover the deductible (Cummins and Tennyson 1996; Weisberg and Derrig 1992). Empirical studies show that higher deductibles lead to the perception that the contract is unethical, that claim exaggeration is fair, and fraudulent behavior is less unethical (Miyazaki 2009).

To mitigate the effects of fraud (e.g., exaggerating claims to recoup one’s deductible), insurance companies attempt to audit suspicious claims. Because auditing insurance claims is costly, auditing procedures are augmented with information obtained from fraud detection systems, typically using various fraud indicators and classification techniques (e.g., Dionne et al. 2009; Schiller 2006). It is therefore crucial for insurance companies to have effective fraud detection systems in place, as a higher accuracy in detecting fraudulent claims can substantially reduce the total costs of ex-post monitoring.

To this end, we propose and test a method for detecting fraud in online insurance claim forms by monitoring users' mouse movements. Mouse movements have been found to give insight into a number of cognitive and emotional processes (see Freeman et al. 2011 for a brief literature review) some of which can result from deception, including decision conflict (McKinstry et al. 2008; Palmer et al. 2013), cognitive competition (Dale et al. 2007; Freeman and Ambady 2009; Freeman and Ambady 2011; Freeman et al. 2008), emotional reactions (Grimes et al. 2013b; Maehr 2008; Rodrigues et al. 2013; Zimmermann et al. 2006; Zimmermann et al. 2003), and increased cognitive processing (Freeman and Ambady 2011). More specifically, in some studies, mouse movements have been proposed to be directly indicative of deception. For example, Valacich et al. (2013) created propositions that explain how mouse movements may be an indicator of deception in concealed information tests; the paper, however, did not test the propositions. Our research contributes to theory and practice by explaining and empirically validating how mouse movements are influenced by deception in online forms.

Theoretical Development and Hypotheses

To develop hypotheses that explain how mouse cursor movements are correlated with fraud, we build on two axioms of deception (fraud being a subset of deception). First, when being deceptive, people normally experience cognitive or moral conflict (Buller and Burgoon 1996; Nunez et al. 2005). For example, one may have feelings of hesitation resulting from guilt or fear of being caught. This may cause people to question their actions, possibly even reconsidering their behavior while moving the mouse to commit fraud (Derrick et al. 2013; Nunez et al. 2005).

Double checking, reconsidering, hesitating, or questioning actions results in deviations from one's intended movement trajectory. The response activation model (Welsh and Elliott 2004) explains how such competing cognitions cause movement deviations. Namely, the model posits that one's hand movements is an aggregate function of all cognitions with actionable potential. Cognitions with *actionable potential* refer to any thoughts, intentions, or other conscious or subconscious cognitions that have even a small potential to result in movement (Welsh and Elliott 2004). For example, when moving the mouse to commit fraud in an online form, one may have a thought to stop the action due to fear of being caught; or, one may have a thought to respond differently (e.g., moving the mouse to select a different option) to result in a more believable fraud. Such thoughts have actionable potential, e.g., to stop or to move differently.

The response activation model explains that when a thought with actionable potential enters the mind (i.e., is in working memory), the mind automatically and subconsciously starts to program a movement response to fulfill that cognition's intention (Welsh and Elliott 2004). This includes transmitting nerve pulses to the muscles to move the hand and realize the intention (e.g., Georgopoulos 1990; Song and Nakayama 2008). These nerve impulses ultimately result in hand movements toward the stimulus. Namely, if a person had no conflicting cognitions of how to move, one's mouse trajectory would roughly follow a straight line from the movement's starting position to the end position (e.g., to the input field on the online form that is to be selected). However, the competing cognitions due to being fraudulent will increase the deviation from this straight line—i.e., the mind programs movement responses toward other stimuli with actionable potential. The deviation can be captured through calculating the *normalized distance* or, in other words, the distance that occurs in addition to the minimum distance[1] required to perform one's movement. In summary, we hypothesize:

H1: When being fraudulent in an online form, people will exhibit greater normalized mouse cursor distance.

[1] When people navigate a page, their movements can be split up into segments. Each segment represents an intended movement between two points. Endpoints of segment are estimated when a person clicks on an element, stops moving the mouse (over 200 ms), or has a drastic change in direction (over a 45 degree change in direction). The starting points include the previous segment's ending point or the mouse's original location when the page loads. A straight line can be drawn between each segment's starting and ending points, which represents the *minimum distance* required to perform one's movement.

The second axiom of deception that we build on is that deception is a complex cognitive process that requires heightened cognitive resources (Carrión et al. 2010). Being fraudulent may entail an individual generating false information while minimizing evidence of deception (Derrick et al. 2011). This requires individuals to not only generate the deceptive information, but also engage in strategic behavior to manage information and image to appear truthful, which overall leads to more cognitive effort and less working memory available for other tasks (Buller and Burgoon 1996). When working memory is decreased, people's reaction times also become slower (Unsworth and Engle 2005). Slower reaction times often lead to slower hand movements (see also the Stochastic Optimized-Submovement Model in Meyer et al. 1988; Meyer et al. 1990). Namely, when reaction time slows, the brain has less time to program corrections to one's movement trajectory when visually guiding the hand to targets. This results in decreased precision in movements or, in other words, greater deviations from one's intended trajectory. One way the brain automatically compensates for this decrease in precision is to decrease the speed of movements (Meyer et al. 1988; Meyer et al. 1990). Hand (i.e., cursor) movement speed and precision are inversely related (Plamondon and Alimi 1997); when speed is reduced, movement precision is increased as the body has more time to perceive and program needed corrections, allowing it to operate optimally within the restriction of slower reaction times (Meyer et al. 1988; Meyer et al. 1990). In summary, we hypothesize:

H2: When being fraudulent in an online form, people will exhibit slower mouse cursor speed.

By the definition of velocity, if distance increases and people move more slowly, this must be a result of taking a longer time to complete the movement (Elert 2014). In addition, when being deceptive, people must take time to engage in strategic behavior, such as generating false information, making sure all of the facts align, and performing other actions to appear credible (Buller and Burgoon 1996). This extra time to perform strategic behavior will increase the overall response time. As a result, we hypothesize:

H3: When being fraudulent in an online form, people will take longer to answer.

Finally, at a higher behavioral level, we predict that when people are providing fraudulent information in an online form (and are unaware that they are being monitored), they will engage in more strategic behavior to ensure that their responses are plausible (Buller and Burgoon 1996). As a result, people may switch between several possible answers in an online context while deciding how to create the most plausible answer. For example, in an online chat context, research has shown that deceivers often make corrections to their responses as a part of engaging in strategic behavior (Derrick et al. 2013). In a mousing context, this behavior results in a greater number of clicks as compared to someone who does not change answers. In summary, we hypothesize:

H4: When being fraudulent in an online form, people will perform more clicks.

Methodology

To test the hypotheses, we conducted a laboratory study within the context of insurance claims. Specifically, participants had to complete a series of tasks in which they were required to file insurance claims—again, insurance claims being a task in which people frequently engage in fraudulent behavior (Dionne and Gagné 2002; Miyazaki 2009). To induce variation in fraudulent behavior, we presented half of the subjects with an honor code (as moral reminders), which has been repeatedly demonstrated to reduce people's tendency to engage in fraudulent behavior (Mazar et al. 2008; Mazar and Ariely 2006). During each task we captured mouse input.

Participants

Fifty-four participants from a large university in Germany participated in the experiment. Each participant received class credit equivalent to an hour of class time as compensation for participating in the experiment. Sixty-nine percent of the participants were male; the mean age was 30.0 years. Fifty-six percent of the participants stated that they have previously claimed damages with insurance companies, and six percent had experience in using online claim forms. Table 1 presents an overview of the descriptive statistics.

Table 1. Description of subjects

Total subjects	54	General claim experience	56%
Gender		Online claim experience	6%
Male	69%		
Female	31%		
Mean age	30.0		

Experimental Design and Materials

Figure 1 provides an overview of the experiment's procedure: Upon arrival at the lab, participants were presented with instructions to complete the experiment (Figure 2). The instructions asked participants to claim damages to their car by using an online insurance claim form. As insurance contracts with a deductible are often perceived to be unfair (e.g., Miyazaki 2009) and therefore induce fraud, we developed an experimental scenario in which participants had a deductible of 600 coins. The initial wealth at the beginning of the experiment was 2,000 coins (see Figure 3 for an example of the scenario). Afterwards, 27 randomly selected participants were presented with an honor code (an established honor/lying manipulation). In particular, the participants in the honor code condition had to sign a statement in which they declare their commitment to honesty before starting the tasks (adapted from Mazar et al. 2008). Manipulating the tendency to engage in fraudulent behavior by using an honor code helped to ensure to obtain variation in the data (lying vs. not/less lying). To control for experimenter bias or demand effects, the participants were tested one-by-one in the lab, where they could input their data anonymously (although they could be tracked by the researchers in another room).

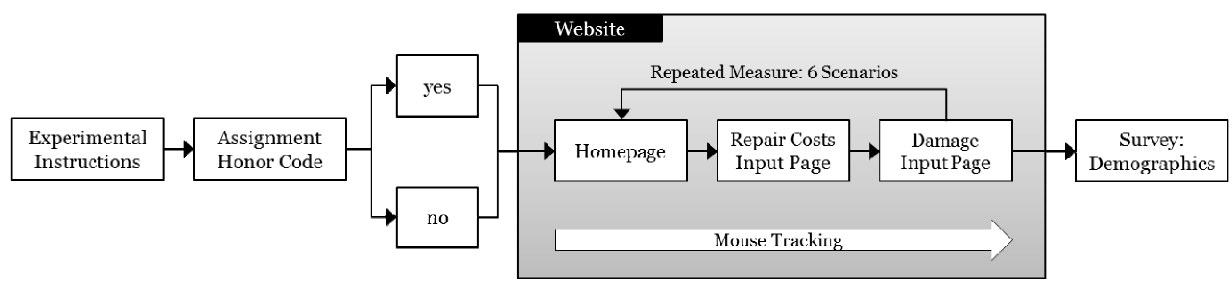

Figure 1. Procedure

After the honor-code manipulation, participants were randomly given six different damage scenarios using a repeated-measures design to parse out variability due to subjects. Further, six levels (scenarios) assured us to get enough observations for the statistical analysis. Each scenario had a different repair cost and a different number of accident damages; though, repair costs and number of accidents were corresponding in an equidistant linear order ranging from 0 costs and 0 damages to 2,000 costs and 5 damages (0/0[2]; 400/1; 800/2; 1,200/3; 1,600/4; 2,000/5) (see Table 2). The applicability of the scenarios was pilot tested with 9 participants using the think aloud method (Jorgensen 1990). To control for learning and sequence effects, we randomized the order of the scenarios. Figure 2 shows an example of a scenario presented to the participants.

After presenting each scenario, participants were directed to a Web page containing an online insurance claim form. The form consisted of a welcome page, a repair costs input page, and a damage input page (for

[2] In Scenario #1 with 0 cost and 0 damage subjects were allowed to commit fraud even though there was no cost and damage.

indicating the location(s) of the damage, see Figure 3). As we were interested in analyzing mouse cursor movements, the pages for entering costs and damage information were designed to require mouse input. On the repair costs input page, the participants could report the costs using drop down menus; on the damage input page, the participants could mark several damages to the rear end of a car (see Figure 3). After completing a scenario, the participants were presented with the next scenario and redirected to the Welcome page. The program started tracking the participants' mouse cursor movements upon visiting the repair costs input page, and stopped recording at the end of each scenario.

After completing all six scenarios, participants were asked to provide demographic information, and were debriefed per IRB protocol.

Situation:

- You have an **initial wealth of 2,000 coins**.
- For your vehicle, you purchased an **insurance policy** with a **deductible of 600 coins**. In other words, if the damage to your car is 1,000 coins, you will be responsible for paying the first 600 coins, and the insurance pays the remaining 400 coins.
- Imagine that recently, you had an **accident** when backing up into a small parking spot, and **damaged the rear end of your car**.
- Now, you have to **file an insurance claim** on the **insurance company's website**.

Example:

- Before the accident, you have an initial wealth of 2,000 coins.
- The repair of the damage to your vehicle costs 1,000 coins; thus, your wealth is reduced to 1,000 coins.
- Assume you file a claim of 1,300 coins. Given your deductible of 600 coins, the insurance would pay you 700 coins (1,300 coins – 600 coins).
- Your final wealth after receiving payment from the insurance company would be 1,700 coins.

Your task:

- You will be presented with 6 different scenarios, for which you will have to file insurance claims. In each scenario, the damage to your vehicle is different.
    - In each scenario, you have an initial wealth of 2,000 coins. The higher your claim, the higher the payment from the insurance company. In other words, **your final wealth depends on the amount you claim from the insurance company**.
    - The insurance company has no way of verifying your claims. Also, the amount of your claims has no impact on future insurance premiums.

Please note:

Please make sure that you understand the instructions provided. All answers provided in this study are strictly anonymous.

Figure 2. Experimental Instructions Sheet (All Instructions Sere in German)

Table 2. Scenarios		
Scenario #	Repair costs (in coins)	Number of accident damages
1	0	0
2	400	1
3	800	2
4	1200	3
5	1600	4
6	2000	5

Scenario 3

You had a damage of 800 coins.

The following areas have been damaged.

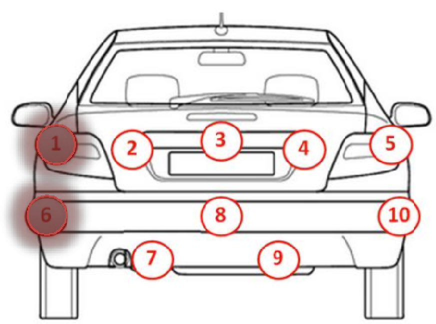

Figure 3. Sample Scenario (Repair Costs: 800; Number of Damages: 2)

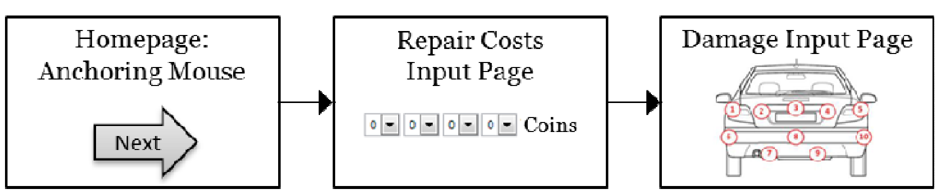

Figure 4. Webpage Sequence

Measures

In each scenario, participants had two opportunities to engage in fraudulent behavior: on the repair costs page and on the damage page (see Figure 4). We operationalized fraudulent behavior as the presence or absence of a positive difference between the actual repair costs/damage and the reported repair costs/damage(s) (for each scenario). Therefore, we defined fraud as a binary variable (1 = fraud; 0= no fraud). We operationalized the extent of fraud as the difference between the reported repair costs/damages and the actual ones (*Repair costs: reported - actual*, *Damages: reported - actual*). On the repair-costs page, 42 percent of the observations (out of 255 observations) were fraudulent. Twenty-one percent of the observations on the repair-costs page were fraudulent.

Using Mouse Recorder Pro (Version 2.0.7.0), we captured each x/y position of the mouse cursor and their corresponding timestamp, which allowed us to calculate the mousing statistics for each participant and scenario. To this raw data, we performed several normalizations. First, we normalized for screen resolution. Although this is not necessary because all participants used the same computer screen in this study, it is a common practice to facilitate future replication (e.g., Freeman and Ambady 2010). We rescaled the x-, y-coordinate pairs to a standard 8 x 6 grid: the x-axis goes from -4 to 4, and the y-axis goes from -3 to 3. The mouse's starting position is mapped at coordinate (0, 0). This maintains the aspect ratio of most screens.

Next, we calculated normalized distance. As participants who claim more must naturally move their mouse further (e.g., marking two damages instead of just one), we normalized for distance by calculating the minimum required distance to perform a person's movement and then subtracting this value from the person's actual distance. This statistic is constructed based on users' actual movements without any required knowledge of whether a response is truthful or deceptive. When people navigate a page, their movements can be split up into segments. Each segment represents an intended movement between two points (e.g., moving the mouse from its current position to a part of a car to select damages). Endpoints of segments are estimated when a person clicks on an element, stops moving the mouse (for over 200 ms), or has a drastic change in direction (over a 45 degree change in direction). The starting points include the previous segment's ending point or the mouse's original location when the page loads. A straight line can be drawn between each segment's starting and ending points, which has a distance (this is referred to as the *minimal distance*). One can then calculate normalized distance by subtracting the minimal distance from the actual distance of the person's movements. This results in a statistic that entails only the "additional" distance that may have been caused by physiological effects of deception, not from simply being required to move the mouse a greater distance to make claims.

Finally, the system calculated the *time* taken for each scenario, *mouse cursor speed* as a function of overall distance and time, and *left clicks*. Table 3 provides an overview of the summary statistics.

Results

Manipulation Checks

Prior to analyzing mouse cursor movements, we performed manipulation checks to ensure that the honor code treatment had the intended effect of reducing fraudulent behavior. We found that participants who were presented with an honor code indeed showed significantly less fraudulent behavior. On the cost page, participants in the honor code condition reported on average 195.23 coins less in repair costs than the participants in the baseline condition ($t = 3.10$, $p < .01$). The difference in mean reported repair cost minus actual repair costs of 220.37 coins was also highly significant ($t = 3.41$, $p < .01$). However, on the damages page, the means for the absolute damages reported and for the reported damages minus the actual damages were not statistically different ($t = 1.09$, $p = .28$ and $t = 1.58$, $p = .12$, respectively). In summary, the honor code effectively reduced the exaggeration of insurance claims when reporting repair costs.

Table 3. Summary statistics

Subsample	Variable	Unit	Mean	SD	p10	p50	p90
Repair Costs Page	Fraud	%	43.36				
	Repair Costs: reported	Coins	1409.15	683.49	400	1400	2200
	Repair Costs: rep. - actual	Coins	199.77	356.94	0	0	600
Damage Page	Fraud	%	20.70				
	Damage: reported	No.	3.32	1.55	1	3	5
	Damage: rep. - actual	No.	0.30	0.70	0	0	1
Subsample	Variable	Unit	Mean	Std. dev.	p10	p50	p90
Repair Costs Page	Normalized Distance	normalized	4.96	5.11	1.44	3.28	11.49
	Speed	px/ms	0.12	0.07	0.05	0.11	0.21
	Time	ms	16295	18230	4804	10693	34848
	Left Clicks	No.	5.00	2.74	3	5	8
Damage Page	Normalized Distance	normalized	7.68	3.86	4.34	6.73	12.16
	Speed	px/ms	0.16	0.06	0.09	0.15	0.25
	Time	ms	13690	9224	5725	11223	23726
	Left Clicks	No.	5.40	2.51	3	5	8

Findings

We next compare the *extent* to which claims were different between fraudulent and non-fraudulent cases (Table 4).[3] In summary, the means of reported damages between the fraudulent (M = 1692.27, SD = 690.28) and non-fraudulent (M = 1186.81, SD = 593.35) cases where significantly different (t = -6.87, p < .01); further, we observed a significant difference in the means of reported vs. actual repair costs between the fraudulent (M = 470.65, SD = 400.77) and non-fraudulent (M = -7.64, SD = 55.57) cases (t = -9.19, p < .01). On the damage page, we found a significant difference in the means of reported damages between the fraudulent (M = 4.40, SD = 1.52) and non-fraudulent (M = 3.03, SD = 1.44) cases (t = -5.72, p < .01); further, there was a significant difference in the means of reported vs. actual damages between the fraudulent (M = 1.45, SD = 0.85) and non-fraudulent (M = 0, SD = 0) cases (t = -8.39, p < .01). In summary, the cases with fraudulent behavior not only significantly exaggerated the actual repair costs, but also reported a higher number of damages, which underlines the argument that participants behave strategically to ensure that their responses are plausible.

[3] Because there were several observations per participant in our study design, it is not reasonable to assume that the observations are independent. For this reason we performed linear regressions of y (e.g., repair costs or damages) on x (Fraud) with standard errors clustered at the participant level to determine whether the differences are statistically significant. This method only assumes that observations are independent between clusters (participants) but not necessarily within clusters. The reported t- and p-values thus refer to the linear regression results with standard errors clustered for each participant.

Table 4. Fraudulent and Non-Fraudulent Cases

			Fraud				
Subsample	Variable	Unit	Mean (no)	Mean (yes)	Mean diff.	*t*	*p* <
Repair Costs Page	Repair costs: reported	Coins	1186.81	1692.27	505.46	-6.87	0.01
	Repair costs: rep. - actual	Coins	-7.64	470.65	478.29	-9.19	0.01
Damage Page	Damages: reported	No.	3.03	4.40	1.36	-5.72	0.01
	Damages: rep. - actual	No.	0	1.45	1.45	-8.39	0.01

Next, we tested our hypotheses to explore whether mouse movements are correlated with fraudulent behavior (Table 5).[4] The results are discussed below.

H1: Normalized Distance—Supported

In fraudulent cases, participants traveled on average a normalized distance of 5.76 on the repair costs page, whereas in non-fraudulent cases, participants traveled significantly less with an average normalized distance of only 4.34 ($t = -1.97$, $p < .05$). Likewise, on the damage page, participants traveled on average a normalized distance of 9.10, whereas in non-fraudulent cases, participants traveled significantly less with an average normalized distance of only 7.31 ($t = -3.30$, $p < .01$). Thus, consistent with hypothesis H1, people exhibited greater normalized mouse cursor distance when being fraudulent.

H2: Speed—Mixed Support

On the repair costs page, participants had an average speed of 0.12 px/ms in fraudulent cases compared to 0.13 px/ms in non-fraudulent cases. Likewise, on the damage page, participants had an average speed of 0.15 px/ms compared to 0.16 px/ms in non-fraudulent cases. Thus, the speed was found to be slower in fraudulent cases than in non-fraudulent cases (on both input pages), which is in line with hypothesis H2. However, the difference was only significant on the damage page ($t = 2.01$, $p < .05$) and not on the repair cost page ($t = 1.56$, $p = .12$).

This may be because the damage page occurs after the repair cost page, and therefore participants must engage in more strategic behavior to ensure the reported damage locations align with the reported damage costs. For example, one must cognitively estimate how much various damage locations would cost so that the reported damage locations would coincide with the reported damage costs. Over- or underestimating the cost of false damage locations would decrease the credibility of the claim. As this activity is more cognitively demanding perhaps than the previous task of reporting the overall damage cost, it will result in slower speed consistent with the theory. Future research should explore this possible explanation in more detail.

H3: Time—Supported

In fraudulent cases, participants took on average 19,519.52 ms on the repair costs page and 16,868.81 ms on the damage page to respond. In non-fraudulent cases, participants took on average 13,853.21 ms on

---

[4] As mentioned in the methodology section, we randomized the order of the scenarios to control for learning and sequence effects. However, to explicitly analyze if our findings are a consequence of a potential learning effect, we also performed empirical tests using the subset of data consisting of only the first observation of every participant (50 observations). These analyses confirm that our findings are not a consequence of a potential learning effect (see Appendix A).

Moreover, we performed additional statistical tests to analyze whether individual characteristics could have affected the results (see Appendix B). We found that there were no statistically significant individual differences between the fraudulent and non-fraudulent cases. Thus, the different mouse usage between the fraudulent and non-fraudulent observations were not likely to be influenced by individual differences.

the repair costs page and 12,855.02 ms on the damage page to respond. These difference were both significant (t = -2.21, p < .05 and t = -2.65, p < .01 respectively). Therefore, H3 is supported; fraudulent cases took significantly longer to respond than non-fraudulent cases.

H4: Clicks—Supported

When committing fraud, participants clicked on average 5.69 times on the repair costs page and 7.09 times on the damage page. When being truthful, participants clicked on average 4.47 times on the repair costs page and 4.95 times on the damage page. This difference between fraudulent and non-fraudulent cases was highly statistically significant for the repair costs page (t = -3.08, p < .01) and the damage page (t = -4.22, p < .01). Thus, consistent with hypothesis H4, we find that fraudulent cases exhibited significantly more clicks than non-fraudulent cases.

Table 5. The Effect of Fraud on Mouse Usage

			Fraud				
Subsample	Variable	Unit	Mean (no)	Mean (yes)	Mean diff.	*t*	*p* <
Repair Costs Page	Normalized Distance	normalized	4.34	5.76	1.42	-1.97	0.05
	Speed	px/ms	0.13	0.12	-0.02	1.56	0.12
	Time	ms	13,853.21	19,519.52	5,666.31	-2.21	0.05
	Left Clicks	No.	4.47	5.69	1.22	-3.08	0.01
			Fraud				
Subsample	Variable	Unit	Mean (no)	Mean (yes)	Mean diff.	*t*	*p* <
Damage Page	Normalized Distance	normalized	7.31	9.10	1.79	-3.30	0.01
	Speed	px/ms	0.16	0.15	-0.01	2.01	0.05
	Time	ms	12,855.02	16,868.81	4,013.79	-2.65	0.01
	Left Clicks	No.	4.95	7.09	2.14	-4.22	0.01

Discussion

This paper explored the following research question: How does fraud in online forms influence mouse cursor movements? Hypotheses were created by building on the response activation model and axioms of deception to explain how normalized mouse cursor distance, speed, response time, and left clicks would be influenced by fraudulent behavior. The paper then presented an experiment to test the hypotheses in an insurance fraud context. The results support all four hypotheses; when being fraudulent in an online insurance form, people exhibit greater normalized distance (H1), slower speed (H2), greater time (H3), and more left clicks (H4) than when being truthful. We will now discuss possible practical and theoretical implications.

Theoretical Contributions

This research contributes to theory by explaining how fraudulent behavior will influence users' mouse movements. Although past literature suggests propositions on how deception may influence mouse movements (e.g., Valacich et al. 2013), this research is among the first to theoretically derive and empirically test specific hypotheses. Building on the response activation model and common axioms of deception, we explain how deception will cause competing hand movements that can be measured via a computer mouse. We posit that people may show hesitancy or experience other conflicting cognitions with actionable potential when being deceptive. As a result, one's movement is a function of not only the primary intended movement, but also these other secondary movements, which will result in deviations from one's intended trajectory. Furthermore, we explain how fraud, as a cognitively demanding task, will result in slower hand movements and more mouse clicks. Hence, this research extends knowledge about how fraud and deception influence hand movements, including speed, normalized distance, time, and left clicks.

Second, we introduce and begin validating a novel measurement of human physiological and psychological states: mouse movements. The results suggest that human states may be inferred through the analysis of mousing and clicking behavior. Aside from the implications for fraud detection, future research could explore what other states can be inferred through analyzing users' mouse movements. For example, research could explore how emotions, ease-of-use, or other outcomes influence mousing behavior and other interactions with a computer.

Practical Contributions

Fraud is ubiquitous and costly in society. As more organizational processes and forms move online, detecting deception in these forms and processes is ever more important. This paper proposes a methodology for detecting deception in online forms based on how people interact with the form via a computer mouse. Namely, this paper explores how being fraudulent influences mouse movement behavior. Capturing mouse movements does not require any special hardware on users' computers; they can be collected in a web browser using common and freely available JavaScript libraries such as JQuery. Hence, this research provides theoretical sound and validated cues of fraud that can increase organizations' ability to identify possible fraud in online forms without substantial investment. This may result in tremendous savings to organizations, customers, and society in general.

Limitations and Future Research

Our experiment results are limited to a sample population that uses a computer mouse. However, other input devices are also popular such as touchscreens, touchpads, sketchpads, and in-air sensors (the Microsoft Kinect® or the LeapMotion®). Much of what is discussed in this paper may apply to these other devices; the technology ultimately captures the location of the cursor (which may include a finger) on the screen, not characteristics specific to a computer mouse. Further, some of these devices capture more sophisticated information than does the computer mouse. For example, a touchscreen can capture the diameter of the finger and thereby infer pressure. In-air sensors capture the z-dimension in addition to the x- and y- dimensions. Future research should explore how human states can be predicted through these other inputs.

Second, this study identified how being fraudulent in an online insurance form is correlated with users' mouse movements. The study did not explore, however, the efficacy of predicting deception based on these mouse movements. Future research should explore this possibility. When predicting deception, one should rely on multiple cues (e.g., clicks, speed, time, normalized distance, and other cues) rather than on a single cue. Speed, normalized distance, time, and left clicks is not an exhaustive list of features that can be calculated from mouse movements. An opportunity exists to explore what other features can be extracted and have utility in predicting users' physiological and psychological responses. Furthermore, no deception detection technique is 100% accurate. Thus, when suspicious behavior is identified through analyzing mouse movements, follow-up investigations should occur to confirm or disconfirm the suspicion.

Third, future research should extend our results to a broader set of contexts and populations. The primary purpose of this experiment was to maximize internal validity. To motivate deception in this controlled experiment, several measures were taken that do not reflect real-life, including explaining that the insurance company could not verify the claim. We recommend future research to extend the external validity of the paper, as generally multiple studies are needed to maximize internal and external validity (Dennis and Valacich 2001). Consistent with our theory, we suspect that the results would be amplified when the probability of being caught is increased, as people will be more likely to double check, reconsider, hesitate, or even question their actions.

Finally, our experiment had participants respond to multiple scenarios and clustered the analysis by participant to calculate significance levels. In real-world insurance scenarios, organizations normally do not have the opportunity to run multiple scenarios with people who submit insurance claims. As an alternative approach to understand people's normal mousing behaviors (and thereby calculate when normalized distance, speed, time, and left clicks change), future research can utilize a control-question approach—i.e., have people answer several questions that they are likely to answer truthfully to establish a baseline. The use of control questions is commonly used in various polygraph-based deception detection approaches (e.g., Abrams 1976; Krapohl et al. 2006).

Conclusion

This paper explored how being deceptive (i.e., fraudulent) in online forms influences mousing behavior. Based on theory relating to deception and the connection between cognition and hand movements, the paper posited that the act of deception has physiological and psychological side effects that can be measured through the computer mouse at a millisecond precision rate. Namely, when engaging in fraud, users travel greater normalized distances, move slower, take more time, and make more left clicks then when providing truthful information. These hypotheses were tested in an online insurance fraud experiment. The results of the experiment supported the hypotheses and suggest that people do behave differently with the computer mouse when committing fraud. Implications regarding the use of mouse movements as an objective measure of behavior in research were discussed. Overall, this research has implications for creating algorithms in the future that detect deception in online forms as a mass-deployable, cost-effective method for identifying fraud.

References

Abrams, S. 1976. "The Control Question: A Technique for Effective Introduction," *Polygraph* (38:1), pp. 13-14.

Barnes, D. 2013. "Identity Theft: IRS Detection Has Improved, Yet Billions Still Lost in 2011 Returns." 2013, from http://www.treasury.gov/tigta/press/press_tigta-2013-39.htm

Buller, D.B., and Burgoon, J.K. 1996. "Interpersonal Deception Theory," *Communication Theory* (6:3), pp. 203-242.

Caron, L., and Dionne, G. 1999. "Automobile Insurance: Road Safety," in *New Drivers, Risks, Insurance Fraud and Regulation,* G. Dionne and C. Laberge-Nadeau (eds.). US: Springer, pp. 175-182.

Carrión, R.E., Keenan, J.P., and Sebanz, N. 2010. "A Truth That's Told with Bad Intent: An ERP Study of Deception," *Cognition* (114:1), pp. 105-110.

Clarke, M. 1990. "The Control of Insurance Fraud a Comparative View," *British Journal of Criminology* (30:1), pp. 1-23.

Coalition Against Insurance Fraud. "The impact of insurance fraud." Retrieved November 1, 2013, from http://www.insurancefraud.org/the-impact-of-insurance-fraud.htm

Coolidge, C. 2006. "Dirty Rotten Scoundrels." Retrieved November 1, 2013, from http://www.forbes.com/forbes/2006/1016/116.html

Cummins, J.D., and Tennyson, S. 1996. "Moral Hazard in Insurance Claiming: Evidence from Automobile Insurance," *Journal of Risk and Uncertainty* (12:1), pp. 29-50.

Dale, R., Kehoe, C., and Spivey, M.J. 2007. "Graded Motor Responses in the Time Course of Categorizing Atypical Exemplars," *Memory & Cognition* (35:1), pp. 15-28.

Dean, D.H. 2004. "Perceptions of the Ethicality of Consumer Insurance Claim Fraud," *Journal of Business Ethics* (54:1), pp. 67-79.

Derrick, D.C., Jenkins, J.L., and Nunamaker Jr, J.F. 2011. "Design Principles for Special Purpose, Embodied, Conversational Intelligence with Environmental Sensors (SPECIES) Agents," *AIS Transactions on Human-Computer Interaction* (3:2), pp. 62-81.

Derrick, D.C., Meservy, T.O., Jenkins, J.L., Burgoon, J.K., and Nunamaker Jr, J.F. 2013. "Detecting Deceptive Chat-Based Communication Using Typing Behavior and Message Cues," *ACM Transactions on Management Information Systems* (4:2), pp. 62-81.

Dionne, G., and Gagné, R. 2002. "Replacement Cost Endorsement and Opportunistic Fraud in Automobile Insurance," *Journal of Risk and Uncertainty* (24:3), pp. 213-230.

Dionne, G., Giuliano, F., and Picard, P. 2009. "Optimal Auditing with Scoring: Theory and Application to Insurance Fraud," *Management Science* (55:1), pp. 58-70.

Dorfman, J. 2013. "Obamacare Will Lift Tax Fraud To A Whole New Level." Retrieved May 1, 2014, from http://www.forbes.com/sites/jeffreydorfman/2013/11/16/obamacare-will-lift-tax-fraud-to-a-whole-new-level/

Elert, G. 2014. *The Physics Hyptertextbook*.

Freeman, J.B., and Ambady, N. 2009. "Motions of the Hand Expose the Partial and Parallel Activation of Stereotypes," *Psychological Science* (20:10), pp. 1183-1188.

Freeman, J.B., and Ambady, N. 2010. "MouseTracker: Software for Studying Real-Time Mental Processing Using a Computer Mouse-Tracking Method," *Behavior Research Methods* (42:1), pp. 226-241.

Freeman, J.B., and Ambady, N. 2011. "When Two Become One: Temporally Dynamic Integration of the Face and Voice," *Journal of Experimental Social Psychology* (47:1), pp. 259-263.

Freeman, J.B., Ambady, N., Rule, N.O., and Johnson, K.L. 2008. "Will a Category Cue Attract You? Motor Output Reveals Dynamic Competition Across Person Construal," *Journal of Experimental Psychology* (137:4), pp. 673-690.

Freeman, J.B., Dale, R., and Farmer, T.A. 2011. "Hand in Motion Reveals Mind in Motion," *Frontiers in Psychology* (2:59).

Georgopoulos, A.P. 1990. "Neurophysiology of Reaching," in *Attention and Performance XIII,* M. Jeannerod (ed.). Hillsdale, NJ: Lawrence Erlbaum Associates Inc., pp. 227-263.

Grimes, G.M., Jenkins, J.L., and Valacich, J.S. 2013a. "Assessing Credibility by Monitoring Changes in Typing Behavior: The Keystroke Dynamics Deception Detection Model," *HICSS-46 Symposium on Credibility Assessment and Information Quality in Government and Business*, Maui, Hawaii.

Grimes, M., Jenkins, J., and Valacich, J. 2013b. "Exploring the Effect of Arousal and Valence on Mouse Interaction," *International Conference on Information Systems*, Milan, Italy.

Jorgensen, A.H. 1990. "Thinking-Aloud in User Interface Design—A Method Promoting Cognitive Ergonomics," *Ergonomics* (33:4), Apr, pp. 501-507.

Krapohl, D.J., McCloughan, J.B., and Senter, S.M. 2006. "How to Use the Concealed Information Test," *Polygraph* (35:3), pp. 123-138.

Maehr, W. 2008. *eMotion: Estimation of User's Emotional State by Mouse Motions*. Saarbrücken, Germany: VDM Verlag.

Mazar, N., Amir, O., and Ariely, D. 2008. "The Dishonesty of Honest People: A Theory of Self-Concept Maintenance," *Journal of Marketing Research* (45:6), pp. 633-644.

Mazar, N., and Ariely, D. 2006. "Dishonesty in Everyday Life and its Policy Implications," *Journal of Public Policy & Marketing* (25:1), pp. 117-126.

McKinstry, C., Dale, R., and Spivey, M.J. 2008. "Action Dynamics Reveal Parallel Competition in Decision Making," *Psychological Science* (19:1), pp. 22-24.

Meyer, D.E., Abrams, R.A., Kornblum, S., Wright, C.E., and Keith Smith, J. 1988. "Optimality in Human Motor Performance: Ideal Control of Rapid Aimed Movements," *Psychological Review* (95:3), pp. 340-370.

Meyer, D.E., Smith, J.E.K., Kornblum, S., Abrams, R.A., and Wright, C.E. 1990. "Speed-Accuracy Tradeoffs in Rapid Aimed Movements: Toward a Theory of Rapid Voluntary Action," in *Attention and Performance XIV* M. Jeannerod (ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, pp. 173-226.

Miyazaki, A.D. 2009. "Perceived Ethicality of Insurance Claim Fraud: Do Higher Deductibles Lead to Lower Ethical Standards?," *Journal of Business Ethics* (87:4), pp. 589-598.

Morley, N.J., Ball, L.J., and Ormerod, T.C. 2006. "How the Detection of Insurance Fraud Succeeds and Fails," *Psychology, Crime & Law* (12:2), pp. 163-180.

Nunez, J.M., Casey, B., Egner, T., Hare, T., and Hirsch, J. 2005. "Intentional False Responding Shares Neural Substrates with Response Conflict and Cognitive Control," *Neuroimage* (25:1), pp. 267-277.

Palmer, C.J., Paton, B., Barclay, L., and Hohwy, J. 2013. "Equality, Efficiency, and Sufficiency: Responding to Multiple Parameters of Distributive Justice During Charitable Distribution," *Review of Philosophy and Psychology* (4:3), pp. 1-16.

Picard, P. 1996. "Auditing Claims in the Insurance Market with Fraud: The Credibility Issue," *Journal of Public Economics* (63:1), pp. 27-56.

Plamondon, R., and Alimi, A.M. 1997. "Speed/Accuracy Trade-Offs in Target-Directed Movements," *Behavioral and Brain Sciences* (20:02), pp. 279-303.

Rodrigues, M., Gonçalves, S., Carneiro, D., Novais, P., and Fdez-Riverola, F. 2013. "Keystrokes and Clicks: Measuring Stress on E-learning Students," in *Management Intelligent Systems,* J. Casillas, F.J. Martinez-Lopez, R. Vicari and F.D.l. Prieta (eds.). Switzerland: Springer, pp. 119-126.

Schiller, J. 2006. "The Impact of Insurance Fraud Detection Systems," *Journal of Risk and Insurance* (73:3), pp. 421-438.

Smith, B.D. 2000. "Insurance Fraud Should be Everyone's Concern," *CPCU Journal* (53:3), pp. 137–138.

Song, J.H., and Nakayama, K. 2008. "Target Selection in Visual Search as Revealed by Movement Trajectories," *Vision Research* (48:7), pp. 853-861.

Unsworth, N., and Engle, R.W. 2005. "Individual Differences in Working Memory Capacity and Learning: Evidence from the Serial Reaction Time Task," *Memory & Cognition* (33:2), pp. 213-220.

Valacich, J.S., Jenkins, J.L., Nunamaker Jr, J.F., Hariri, S., and Howie, J. 2013. "Identifying Insider Threats through Monitoring Mouse Movements in Concealed Information Tests," *HICSS-46 Symposium on Credibility Assessment and Information Quality in Government and Business*, Maui, Hawaii.

Weisberg, H.L., and Derrig, R.A.-. 1992. "The System Misfired," *Best's Review*), December, 37-40.

Welsh, T.N., and Elliott, D. 2004. "Movement Trajectories in the Presence of a Distracting Stimulus: Evidence for a Response Activation Model of Selective Reaching," *The Quarterly Journal of Experimental Psychology* (57:6), pp. 1031-1057.

Zimmermann, P., Gomez, P., Danuser, B., and Schär, S. 2006. "Extending Usability: Putting Affect into the User-Experience," *Proceedings of NordiCHI'06*, pp. 27-32.

Zimmermann, P., Guttormsen, S., Danuser, B., and Gomez, P. 2003. "Affective Computing-A Rationale for Measuring Mood with Mouse and Keyboard," *International Journal of Occupational Safety and Ergonomics* (9:4), pp. 539-551.

Appendix A: Analyses Regarding a Potential Learning Effect

Table A.1 and A.2 report the results corresponding to Table 4 and 5 in the paper if only the first observation of every participant was used.

Table A.1. Comparing Fraud Groups

			Fraud				
Subsample	Variable	Unit	Mean (no)	Mean (yes)	Mean diff.	*t*	*p*
Repair Costs Page	Repair costs: reported	Coins	1608.57	1980	371.43	-2.28	0.03
	Repair costs: rep. - actual	Coins	-14.29	460	474.29	-3.98	0.01
Damage Page	Damages: reported	No.	4	5.14	1.14	-2.35	0.05
	Damages: rep. - actual	No.	0	1.29	1.29	-6.97	0.004

Table A.2. The Effect of Fraud on Mouse Usage

			Fraud				
Subsample	Variable	Unit	Mean (no)	Mean (yes)	Mean diff.	*t*	*p*
Repair Costs Page	Normalized Distance	Normalized	4.97	8.66	3.68	-2.07	0.04
	Speed	px/ms	0.08	0.08	0.00	-0.38	0.70
	Time	Ms	21519.11	34829.93	13310.80	-1.85	0.07
	Left Clicks	No.	5.86	8.07	2.21	-1.62	0.11

Subsample	Variable	Unit	Fraud Mean (no)	Fraud Mean (yes)	Mean diff.	*t*	*p*
Damage Page	Normalized Distance	normalized	9.32	13.49	4.17	-2.44	0.02
	Speed	px/ms	0.12	0.10	-0.02	1.04	0.31
	Time	Ms	19882.98	30524.71	10641.70	-3.33	0.00
	Left Clicks	No.	6.53	8.57	2.04	-3.08	0.00

- The results remain qualitatively unchanged if only the first observation for each participant is analyzed. The coefficients of the mean differences remain identical for all mouse variables except Speed on the repair costs page (which is, however, not significantly different from zero in both analyses).
- The magnitude of the coefficients is in most cases similar or even higher compared to the findings presented in the (original) Table 6.
- While several of the presented differences remain statistically significant, some results are not significant anymore, which is mainly due to rather small number of observations (only 50 observations if only the first observation per participant is used compared to 255 observations if all observations are used).

Appendix B: Analyses Regarding Potential Individual Differences across Fraudulent and Non-Fraudulent Cases

To analyze whether individual characteristics (see Table 2) could have affected the results, we performed statistical tests exploring whether these characteristics differ between the fraudulent and non-fraudulent group. The results are reported in Table B.1

Table B.1 The Effect of Fraud on Mouse Usage

Variable	Unit	Fraud Mean (no)	Fraud Mean (yes)	Mean diff.	*p*
Gender	Percent Male	71%	53%	-18%	0.25
Age	Years	30.0	29.3	-0.6	0.80
General claim experience	Percent	51%	67%	15%	0.33
Online claim experience	Percent	0%	20%	20%	0.08

We find that there are no statistically significant individual differences across the fraudulent and non-fraudulent group. Thus, the different mouse usage between the fraudulent and non-fraudulent observations are not likely to be influenced by individual differences.