Reporting Spam Calls and Texts: A Comparative Study of the U.S. and South Korea

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Extended Abstract

Reporting of unsolicited spam calls and texts to relevant authorities plays an important role in mitigating misinformation and scams. In particular, immediate reporting after receiving a spam benefits reporters and authorities to respond to future spams effectively. To investigate key factors that are associated with immediate or delayed spam reporting, this study analyzes large-scale real-world datasets from two organizations: FCC (Federal Communications Commission, U.S.) and KISA (Korea Internet and Security Agency, South Korea). The results of logistic regression analysis reveal that 1) ready access to the spam reporting system significantly facilitates reporters' immediate reporting and 2) sound-type spam messages have a higher likelihood of immediate reporting than text-type spam messages. Our findings are consistent with existing theories, and we draw practical implications that could improve existing spam reporting systems.

Keywords

mobile, spam, reporting, FCC, KISA, comparative study

Introduction

Cyberattacks and digital fraud attempts are getting prevalent as related technologies advance. Internet Crime Complaint Center, an official entity operated by the U.S. Federal Bureau of Investigation reports they have aggregated 1,707,618 complaints in total with $10.2 billion losses over the years 2015 to 2019 (Gorham 2019). In particular, unsolicited calls and scam text messages with malicious URLs have been a thorn among cell phone users, giving rise to disturbing attention, personal information leakage, and financial damages at the worst (FCC 2019a; FCC 2019b). Caller ID spoofing (Mustafa et al. 2016), smishing (Yeboah-Boateng and Amanor 2014), and vishing (Reed 2019) are the typical tricks that victimize mobile phone users, which is mostly based on automated dialing and text transmission techniques.

To address the phone-based security risks, public authorities have been developing systems where phone users are able to report details of the attack such as text messages received, the time when the message arrived, and the sender's number. For example, the Korea Internet and Security Agency (KISA) has implemented a system named Mobile Spam Easy Report (MSER) starting from February 2007 (KISA 2020). The system enables Android system users to file any suspicious messages to the agency automatically by directly selecting the message itself without a need to visit additional web pages. According to the survey conducted by Korea Communications Commission in 2018, the average number of spam that a mobile phone user receives on a daily basis are 8.15, and 71.1% of survey respondents are satisfied with MSER as of second half of 2017 (KCC 2018).

Federal Communications Commission (FCC), an agency of the U.S. government that regulates the communication industry, has also offered the Phone Complaint reporting system to collect complaints about ill-intentioned text messages and spoofing swindle cases (FCC 2020). The system allows users to submit communication troubles associated with unwanted calls or privacy concerns, including a reporter's personal email address and attachments, covering a variety of issues such as junk faxes, cramming (unauthorized charges on the phone bill), and interference, to name a few. Compared with the mobile interface provided by KISA, the FCC system is limited to access through a website and requires users to feed details of the incident manually.

Our key research question is: What factors affect the immediate or delayed reporting of spam messages? Data has been collected from the aforementioned two systems, and we focus on the time between when the spam was received and when it was reported. We look at the characteristics of the calls and the time when the spam call occurred to predict if the spam will be reported immediately or delayed.

Theory

Immediate Gratification

The effort of reporting a spam benefits a reporter by reassuring him/herself that the message and corresponding victimization have been notified to the concerned authorities. The effort also helps the authorities to identify spammers and take proper steps to mitigate potential frauds. Accordingly, the faster a reporter completes a report, the sooner he/she and the authorities get benefits. However, in practice, a reporter's prompt reporting behavior is prone to be discouraged by the several inconveniences that require a reporter to access a spam reporting system (i.e., FCC Phone Complaint website) and fill in the form that lists a number of input fields such as reporter's personal name, issue description, and time of the issue, to name a few. On the other hand, delaying spam reporting may also cause inconvenience of retrieving a certain message or recollecting whether it was a spam or not. As a result, two types of behavioral decision making are defined in this context; immediate versus delayed reporting. Immediate reporting is when the reporting happens soon after receiving and identifying a spam. By comparison, delayed reporting is the behavior that postpones the completion of the reporting for any reason. Immediate or delayed reporting is relative and is based upon the total range of the reporting time observed in our data.

The theory of immediate gratification explains why delayed reporting happens from reporter's perspective (Acquisti 2004). Immediate gratification is a preference of instantaneous utility (O'Donoghue and Rabin 2000). In our context, the utility can be described as an individual's pursuing of prompt comfort and gratification by reporting a spam to the reporting system as soon as identifying it, rather than waiting and losing the value of the report to the society.

Perceived Behavior Control

Performance of a human behavior is affected by the presence of available resources and one's ability to control the given conditions (Hardin-Fanning and Ricks 2017). This notion has been conceptualized as the perceived behavior control (PBC), which is the person's perception as to how easy or difficult performance of the behavior is likely to be (Ajzen and Madden 1986). According to PBC, the more resources and fewer obstacles a person can hold, the greater should be his/her perceived control over the behavior. The resource can involve enough time, money, equipment, or specific technologies that can assist performing a target behavior (Taylor and Todd 1995). Traditionally, PBC has been treated as an element of the theory of planned behavior, the extension of the theory of reasoned action. The theory of planned behavior is a social psychological model of purposive behavior and deliberative decision making. Thus, PBC allows us to view our research topic as a matter of whether the temporal accessibility of the system has an impact on people's immediate reports to FCC and KISA.

Cognitive Load Theory and Modality

Humans serially process information one at a time, not in parallel, when solving a problem (Simon 1978). This process is characterized by a small short-term memory (i.e., working memory (Baddeley 1992)) due to the limited capacity of information processing that an individual possesses. A problem solver therefore tends to pursue the sequential search with a small amount of information, minimizing cognitive resources needed to find answers to the problem.

In this sense, the cognitive load theory (CLT) proposes three types of cognitive load (intrinsic, extraneous, and germane) and demonstrate those cognitive load factors influence information processing tasks such as learning, memory, and communication (Sweller 1994; Sweller 1998). Among the types, extraneous cognitive load is known to be concerned with the manner on how the information is presented (Chandler and Sweller 1991; Sweller 1998). If the way of providing a certain piece of information increases extraneous cognitive load, it is more likely to impede an individual's intellectual ability of handling the information promptly.

For our study, we connect the modality of the spam message (text or sound) to extraneous cognitive load, assuming that sound-type spam message would be comparatively easier for a reporter to file immediately. This assumption is supported by several studies (Cao et al. 2009; Castro-Alonso and Sweller 2019; Lin and Yu 2017; Liu et al. 2019; Rummer et al. 2011; van der Heiden et al. 2020), which prove sound modality's relative reduction of cognitive load, compared to text modality.

Method

A target variable of our interest is *Immediate Reporting* that explains whether the reporting is completed without delays by an individual reporter or not. The value of *Immediate Reporting* is dichotomous; immediate or delayed. The way we define 'immediate' or 'delayed' for each dataset is shown in Data section below. The first predictor is *Time Active* that articulates whether both date and time when a reporter received the spam allow him/her to be reasonably capable of accessing the reporting system. *Message Type* is the second predictor, which is either text or sound. In this respect, binary logistic regression is performed for the statistical analysis. We hold all the variables and analysis method consistent in two datasets.

Based on the research question, related theories, and research variables defined, we develop the following two hypotheses for the study. **H1**: *Ready access to the reporting system is positively related to immediate reporting behavior.* **H2**: *Sound-type spam messages have the higher likelihood of immediate reporting behavior than text-type spam messages.*

FCC dataset

We collect two datasets from FCC and KISA, respectively. This section presents the characteristics of the dataset and details of data processing to obtain our target variable and predictors.

FCC dataset specifically indicates 'Consumer Complaints Data – Unwanted Calls' provided by Consumer Inquiries and Complaints Division of FCC. Individual complaint has been filed with the Consumer Help Center from October 31, 2014. We accessed this repository on May 14, 2020 and downloaded 958,684 reports.

After removing incomplete records, we create a new variable, *Issue Happened* after combining the value of *Date of Issue* (i.e., the date when a reporter received a spam) and *Time of Issue* (i.e., the time when a reporter received a spam). We keep statistical outliers as the research goal is to explore both instantaneous and belated decision-making behaviors that should be located at the extremes among observations.

Then, another new variable, *Time Spent before Reporting* (TSR) is computed by subtracting the value of *Report Created* (i.e., the time and date when the complaint was reported to the FCC) from the value of *Issue Happened*, as the natural log scale (ln). We operationally define lower 10% of TSR (less than or equal to 15,444.00 seconds) as a group of immediate reporting (n = 29,447), while upper 10% of TSR (more than or equal to 248,017.00 seconds) as a delayed reporting group (n = 27,746). Accordingly, the dependent variable, *Immediate Reporting* is set to 1 if the reporting is immediately completed. Otherwise, *Immediate Reporting* is labeled 0.

Regarding the independent variables, we create the *Time Active* variable that indicates whether both date (*Date of Issue*) and time (*Time of Issue*) when a reporter receives the spam reasonably allow him/her to be capable of accessing the reporting system. If a reporter gets the spam between 8 am and 5 pm on a normal weekday, the value of *Time Active* is set to 1, otherwise (between 5 pm to 8 am, weekends, or U.S. federal holidays), the value is coded as 0. For *Message Type*, another independent variable, we group the responses of *Type of Call* into 'text' or 'sound.'

KISA dataset

In partnership with KISA, we were provided the dataset generated on January 10, 2020, which contains 135,911 reports with obscured personal information. We derive *Time Spent before Reporting* (TSR) variable on the natural-log scale by subtracting the value of *Time of Issue* from the value of *Report Created* in each record. The data set has been cleaned by removing records that contain inaccurate or missing data points while keeping statistical outliers. As a result, we assign lower 10% of TSR records (less than or equal to 27.00 seconds) as an immediate reporting group (n = 14,053), and upper 10% (more than or equal to 175,961.40 seconds) as non-immediate reporting group (n = 13,562). *Immediate Reporting* is 1 if a reporter submits a report immediately, otherwise, *Immediate Reporting* is coded as 0.

For the independent variables to match with FCC data, the *Time Active* is derived from the corresponding *Time of Issue* value. If a reporter receives the spam message at any point from 8 am to 5 pm on a weekday, the code of *Time Active* marks 1. On the contrary, once a spam is sent at either between 5 pm to 8 am, weekends, or South Korea's official holidays, the code is 0. *Message Type* (text or sound) is determined based on *Message Type* variable. The final size of each variable obtained from FCC and KISA data is tabulated in Table 1.

Table 1. Size of variables in each dataset

Variable	Value	Code	Dataset	
			FCC	KISA
Immediate Reporting	immediate	1	29,447	14,053
	delayed	0	27,746	13,562
Received Active	active	1	43,405	20,961
	non-active	0	13,788	6,654
Message Type	sound	1	53,492	13,984
	text	0	3,701	13,631
total			57,193	27,615

Results

The logistic regression model using FCC dataset shows a statistical significance with $\chi^2(2) = 1023.579$ and $p < .0005$. The value of Cox & Snell R Square and Nagelkerke R Square is 0.018 and 0.024, respectively. The estimated logistic regression model is, *predicted logit of Immediate Reporting = 0.940 + 0.455 * Received Active + 0.698 * Message Type*. The odds ratio for the *Received Active* coefficient is 1.576 and significant at $p<.0001$. This implies that if a reporter receives a spam at active time slots, he/she is 1.576 times more likely to report immediately than a reporter who received spam during non-active time slots. Similarly, the odds ratio for the *Message Type* is 2.010 with a significance of $p<.0001$. This suggests that sound type message is 2 times more likely to be immediately reported compared to text type message.

In KISA dataset, the logistic regression model is statistically significant with $\chi^2(2) = 3747.891$ and $p < .0005$. The value of Cox & Snell R Square is 0.127 and Nagelkerke R Square is 0.169. The estimated logistic regression model is, *predicted logit of Immediate Reporting = -1.049 + 0.534 * Received Active + 1.342 * Message Type*. The odds ratio of the *Received Active* coefficient is 1.706 and significant at $p<0.0001$. Thus, when a reporter receives a spam during active time slots, immediate reporting is 1.706 times more likely to happen than when spam is received during non-active time slots. In terms of the odds ratio of the *Message Type*, the value is 3.827 and significant at $p<.0001$. In other words, a sound type spam message is 3.827 times more likely to be immediately reported than text type spam message. These results confirm analogous patterns between variables of FCC dataset.

Discussion and Future Direction

To our knowledge, this study is the first empirical investigation on spam reporting behavior using large real-world datasets from concerned authorities; FCC and KISA. We analyze the similarities and differences of the datasets, deriving common variables and developing statistical models to make the analysis comparable.

It is hypothesized that 1) ready access to the spam reporting system is positively related to immediate reporting behavior, and 2) sound-type spam messages have a higher likelihood of immediate reporting behavior than text-type spam messages. To explore such assumptions, we perform a logistic regression analysis as operational definition of dependent variables is dichotomous; immediate or delayed. The results of FCC dataset support our hypotheses that the immediate reporting is more likely if 1) an individual gets a spam message during active hours and 2) the message type is sound. The results of KISA dataset confirms the findings with statistical significances once again.

Theoretically, our findings are consistent with background knowledge examined. Firstly, regarding immediate gratification, it is obvious that two types of behavioral decision making exist in spam reporting context - immediate or delayed reporting. It suggests reporters tend to report spams without delays in order to sidestep inconveniences caused by the increased efforts and discomforts (e.g., retrieving and recollecting the spam messages).

Secondly, the theory of perceived behavior control can also explain the reasons for immediate reporting. The theory posits that the presence of available resources and abilities to manage the given conditions acts on the performance of a human behavior. In our study, it is found that if an individual receives the spam message at the time that makes him/her access to the reporting system reasonably, the immediate reporting behavior is significantly carried out.

Lastly, the study proves the impact of sound modality's relative reduction of cognitive load on the immediate reporting behavior. Cognitive load theory proposes that if the way of presenting information increases extraneous cognitive load, the level of an individual's intellectuality would decrease. We associate a spam message's modality (sound or text) with extraneous cognitive load and assume that sound message type would stimulate immediate reporting. The statistical analysis demonstrates that sound-type spam messages have a higher likelihood of immediate reporting behavior than text-type spam messages.

A notable difference of the results between FCC and KISA dataset is the sound message type's magnitude of the impact on immediate reporting. Sound messages in KISA dataset show greater magnitude of the influence on immediate reporting than those in FCC dataset. This discrepancy might have arisen from the fact that KISA report only includes mobile phone spam messages, while FCC report contains spam messages collected from not only mobile but also land-line telephone. A number of studies report that people generally perceive mobile phone more private than land-line phone (Przybylski and Weinstein 2013; Srivastava 2005). Therefore, the chances are spam message could be more alarming to mobile phone users, compared to land-line phone users who are used to share the phone with other people.

For deeper understanding of spam reporting behavior, we plan to make better use of the source data. Raw FCC dataset (Consumer Complaints Data), to be specific, contains reporter's location information at the level of zip code, which had not been explored in this study. The location data could help us to quantify the susceptibility of the unsolicited spam attack by state and provide analytical warnings to vulnerable governments.

Meanwhile, KISA dataset (Mobile Spam Easy Report) contains spam text messages that reporters actually received on their mobile devices. Natural language processing with such text data is expected to disclose not only characteristic narrative of unwanted spam but also the impact of the personally targeted message on immediate or delayed reporting. Accordingly, gathering additional spam report data from both organizations is a key to the follow-up study.

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