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RESEARCH ARTICLE

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Consumers' response to mass market scam solicitations: profiling scams and responses

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ABSTRACT

Mass marketing scams (MMSs) impact millions of people with financial losses in the billions. Understanding what types of MMSs work is key to reducing the compliance rate. Inspired by Simon's work, we designed an experiment to examine how four different types of MMSs impact interest in and intention to respond to solicitations. We first conducted a cluster analysis on 215 actual MMS solicitations. The analysis revealed four distinct types of solicitations: negative-cold, one-reward letters, high emotionality, high scarcity letters where the prize is mentioned often, very colorful multi-prize letters, and low emotionality, low scarcity cold letters. In a second experiment, 281 participants (recruited on MTurk) were randomly assigned to read one of the four types of solicitations. Our data revealed differences in intention to respond by sending money. Furthermore, younger (vs. older) individuals indicated a higher interest in the solicitation and higher intention to send in money and rated the solicitations as significantly more beneficial and less risky. Finally, perceptions of risks and benefits were the main driving force behind compliance beyond interest and intention to comply. In line with Simon's ideas, our study highlights the need to examine both the environment (the types of solicitations) and the decision-maker.

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Cluster analysis; fraud; need for cognition; mass marketing solicitation

Introduction

Mass marketing scams (MMSs) victimize millions of individuals across the globe each year and are associated with financial losses in the hundreds of millions (Anderson, 2016). The Federal Bureau of Investigation has also identified what it calls the 'hallmarks' of MMSs, in an attempt to reduce the number of people falling prey to scammers: (i) 'Offers appear 'too good to be true,' (ii) payment for goods or services are required in advance, (iii) personal information is requested over the telephone, (iv) offers are unsolicited, and (v) representatives use high-pressure sales techniques, claiming that immediate action is required (Federal Bureau of Investigation, 2021). The purpose of this current project was to understand features of mass marketing solicitations using cluster analysis and how different

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clusters impact individuals' compliance with these solicitations. In experiment 1, we employed cluster analysis to detect and reveal patterns that characterize MMS solicitations using bottom-up content analysis techniques. Building on our findings, in experiment 2 we experimentally investigated how the different clusters that were identified in study 1 impact consumers' intention to reply to different MMSs.

Analysis of scam

To address fraud's financial, health, and psychological impact (Button, Lewis, & Tapley, 2014), on millions of people across the globe, several researchers have developed conceptual models or analyzed existing data sets to reach a better understanding of the phenomena. Jones et al. (2015; see also Moreno-Fernandez et al., 2017) have suggested that three factors underlie individuals' willingness to respond to an MMS solicitation: (i) persuasive techniques employed by the sender, (ii) information processing of the user, and (iii) 'userX,' that is, the human–computer interaction or consumer/solicitation context. The authors' intuition resonates well with Simon's (1990, p. 7) intuition that decision-making is 'shaped by scissors whose blades are the structure of task environments and the computational capabilities of the actor.' What Simon and others have come to advocate is the idea that it is not enough to study human cognition and information processing, but we must, in conjunction, investigate the nature of the environment(s) that individuals live in. Building on this important idea, several researchers have come to examine the link between human decision making and the environment in which they operate (e.g. Gigerenzer & Todd, 1999; Payne et al., 1993). Gigerenzer and Goldstein (1996), for example, have shown that different decision strategies can be applied to different decision environments and that simple decision rules, for example, can perform well in certain environments but not in others. Likewise, whether a decision environment is information-rich or information-poor (Lurie, 2004), certain or uncertain (Farrar et al., 2018), emotion-rich or poor (Slovic et al., 2007) all tends to impact the decision-maker. One can, thus, view Cialdini's work on persuasion as an extension of this line investigation, as it indicates the type of conditions that influence the decision-maker. For example, decision entrainments that are laden with emotions, scarce, and contain a reference to authority might receive different responses compare to environments that are cold, abundant, and lack authority. Thus, when examining why people fall prey to fraud there is a clear need to investigate both the environment in which the decision-maker operates – that is, the structure of the fraud solicitation – as well as the decision-maker. In the present study, we capitalize on this idea and analyze first the environment in which the decision-maker operates – that is, the MMS – and then examined how individuals respond to different MMSs.

Previous investigations have used content analysis to help gain insight and detect fraud behavior on both the individual and the organizational level. Churyk et al. (2008) analyzed accounting and auditing reports from 68 organizations to detect whether these organizations had employed deceptive or fraudulent strategies. Their data identified linguistic characteristics that can help differentiate between honest and deceptive (e.g. Enron) organizations' reports. Focusing on MMSs, Chang (2008, p. 71) evaluated six MMS solicitations that he personally received. His investigation revealed that fraudsters tend to use techniques that 'include assertion of authority and expert power, mimicking and referencing persons/organizations, providing partial proof/legitimacy, reasoning, reciprocation, creating urgency, and implying scarcity.' While the studies of Churyk et al. (2008) and Chang (2008) are very valuable, they are limited in their relevance (corporate reports cannot shed light on compliance with MMS solicitations), their scope (six letters), and/or their lack of experimental methodology. That is, earlier work tended to focus on one blade of Simon's scissors and failed to evaluate how different environmental structures – or types of MMS letters – impact the decision maker's willingness to respond to them.

Scam and cluster analysis

One type of content analysis, cluster analysis, has been used extensively in biology, marketing, and computer science. Cluster analysis has also been applied to examine different types of fraud, such as credit cards, health insurance, and accounting (see Sabau, 2012). In essence, cluster analysis is a technique that allows researchers to group a set of data objects into a cluster without having to specify any a priori assumptions. That is, the method can be used to organize data into meaningful, interpretable groups. Because cluster analysis always groups the data, it is an excellent exploratory method of finding patterns in the data. A good cluster will have high similarity within the cluster but be different from other clusters. While there are many classification methods in clustering, in the present investigation we used exclusive clustering, meaning that each solicitation letter received only one cluster value. To our knowledge, this is the first time a cluster analysis methodology has been applied to MMSs. As such, it was possible that the letters would not group into meaningful clusters, which could represent an important finding in itself. However, this technique allowed us to examine whether different types of MMSs are more effective (i.e. generate higher rates of compliance) depending on certain linguistic characteristics that are specific to each MMS. Importantly, these letters were then used to examine which cluster leads to the highest rate of compliance – that is, the likelihood of responding to the offer.

While cluster analysis is useful for understanding the structure and design of MMSs, it provides little to no insight into how people process and react to them. This is an important omission, as MMSs differ along with several variables, such as the amount of money they offer, the urgency of response, and their emotional tone, among others. Thus, to provide a more comprehensive picture there is a need to examine not only the content of the solicitations but also how people respond to them. After all, different MMSs might activate different cognitive and emotional information processing. For example, letters that are perceived to be businesslike (labeled 'cold' or colorless) compared to those that are 'fun' and colorful (labeled 'hot'; Wood et al., 2018), or that contain a sense of scarcity (e.g. 'act now') could activate different processing and hence different levels of compliance (Cialdini, 2007).

Scam compliance

To date, several studies have investigated what factors impact compliance with MMSs. Wood et al. (2018; see also Modic & Lea, 2013) presented participants with MMSs that differed in either their scarcity or their authority (known vs. unknown organization). In a second study, the authors manipulated the size of the activation fee participants were asked to pay to receive their so-called prize. In addition, Wood et al. (2018) has examined individuals' perceptions of the risks and benefits of different MMS (on a scale from 1-10) as well as a range of demographic factors. The results show that neither scarcity nor authority impacted the likelihood of responding to these solicitations. In contrast, the presence of an activation fee (whether it was low, medium, or high) significantly reduced participants' willingness to contact the activation number. Furthermore, participants' perceptions of risks and benefits were the main driving force in explaining their intention to contact the activation number.

A somewhat similar study (Jones et al., 2019) – examining responses to real and phishing (deceptive messages that trick people into revealing personal details) emails – manipulated both time pressure (either given 5 min or told to take their time) and the legitimacy of the emails (Phishing one and legitimate emails) and included a battery of cognitive measures. Jones et al. (2019) found that time pressure negatively impacted participants' ability to discriminate between real and fake emails and that the cognitive reflection test was predictive of participants' ability to discriminate between real and fake emails. Counter to expectation, other measures (e.g. sensation seeking, flanker test, Stroop task, reading skills) failed to predict participants' behavior.

An earlier investigation by Fischer et al. (2013) examined the content of real scams and their influence on the likelihood of responding to them. After reviewing over 580 different scams, Fischer et al. (2013) reported that fraudsters often employed 'emotional cues, trust and authority cues, cost–benefit considerations (size of the prize), behavioral commitments, and sunk–cost considerations' (p. 2063). Building on these findings, the authors categorized eight types of scams that vary in their information: whether the scam offer appeared early or later, prize amount, symbols of authority, and triggers of positive emotions. Next, the authors evaluated how each one of the eight scams impacts the likelihood of individuals responding to these scams. The data revealed little variation in response rate about the eight types of scams.

Taking a somewhat different approach, Button, Nicholls, Kerr, and Owen (2014) conducted interviews and focus groups with fraud victims as well as professionals to better understand why individuals fall prey to scams. Their qualitative method identified 'the diversity of frauds, small amounts of money sought, authority and legitimacy displayed by scammers, visceral appeals, embarrassing frauds, pressure and coercion, grooming, fraud at a distance and multiple techniques' (2014, p. 391), as the key factors associated with becoming a victim of scams.

Focusing on 419 scams (better known as the Nigerian scam), Isacenkova et al. (2014) investigated the evolution and dynamic nature of these types of scams. Using an available data set (419scam.org), they were able to analyze over 36,000 scam messages across 12 countries. Using cluster analysis, the authors were able to group the different scams into types, means used to contact potential victims (emails, phone, etc.), duration of the scam campaign, and country of origin. While Isacenkova1 et al. work can provide important insights about the nature of 419 type scams, their work is somewhat limited. First, it only examined limited factors (country of origin, length of the campaign, etc.), but have not evaluated the wording of the message. Second, they did not examine how different factors impact individuals' likelihood of responding to these scams.

Despite the growing body of work on fraud, a review of the literature by Norris et al. (2019) maintained that there is still a paucity of data on which psychological mechanisms predict susceptibility to fraud. Norris et al. (2019) also championed the idea that one needs to examine both the message (e.g. the MMS solicitation) and the person if one is to uncover the factors associated with susceptibility to fraud. After all, MMSs come in many different forms, with some letters being colorful and emotional and others cold and calculated. The use of a generic letter might not capture the richness and diversity of the different MMSs that exist and might not be the appropriate approach when trying to uncover the factors that influence susceptibility, as different types of MMSs may lead to different response rates for different individuals. Taken together, these ideas suggest that by examining the different types of letters used by fraudsters, one might be able to identify the techniques used by scammers and to pinpoint the one(s) that individuals are more likely to fall prey to.

To examine our aims, we have conducted a study with two experiments. In experiment 1, we completed a cluster analysis of 215 letters to classify them into separate clusters. In experiment 2, we used the results from study 1 to experimentally evaluate how the different clusters (i.e. types of letters) impact individuals' willingness to respond as well as their perceptions of the risks and benefits associated with these MMSs. Given the exploratory nature of the cluster analysis, we did not have any a priori hypotheses.

Experiment 1

Procedure

Cluster analysis variables

Based on past literature, it was determined that the following variables would be extracted and used in the cluster analysis: prize amount and number of times a prize is mentioned, the length of time that the individual had to send in the activation amount, scam letter type (cash prize, sweepstakes, romance, or gift/service), text attributes (more on attributes below), and the amount of color in the letter.

While most of the variables were extracted programmatically, a few were extracted by one of the authors or through examination of each letter individually. Prize amount, activation amount, prize mention frequency, and the length of time for activation were gathered by hand. Additionally, the type of scam letter was input after reading the letter. The categories for the type of scam letter were chosen from a list of the most common ones identified by the U.S. Postal Service.

The attributes of the text were believed to be an important distinguisher between different clusters. To examine the emotionality of the text, the physical letters were scanned and saved as PDFs to help extract the text from them. The content of the letters was then put through the NRC emotion lexicon database (see, https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm) to gather the emotionality of the text. The NRC database is a dictionary of words and their respective emotion associations. The emotions extracted from the database are positive, negative, anger, anticipation, disgust, fear, joy, sadness, and trust. It has been validated through multiple studies and was normed on Amazon Mechanical Turk (MTurk; Mohammed & Turney, 2013). The resulting output gave a total emotionality score for each emotion for each letter. These totals were then divided by the total number of words in the letter to show the proportion of the letter that contained each emotion. In addition to the emotionality of the letter, the length of the letter, and the proportion of the letter that contained 'scarcity' words were input in the analysis.

The other information that was extracted from the letter through coding was the amount of color in the letter. This variable was extracted by examining each pixel in the letter and categorizing it as being either color or noncolor (e.g. white, gray, or black). The variable that was put into the cluster analysis was a continuous variable that represented the proportion of the letter that was colorful, or hot, compared to non-colorful, or cold. While we collected data about the number of sheets of paper contained in the letter, the hotness/coldness of the envelope, and if the letter contained a return envelope, this information was not included in the final analysis.

The optimal number of clusters

A total of 215 letters were gathered for the cluster analysis. A final list of nine variables was entered in the cluster analysis: the reward of the letter; if the letter offered multiple rewards (coded as a binary yes/no: 1 or 0); how often the reward was mentioned; the activation amount; the date by which the activation fee needed to be paid; the word count in the letter; the proportion of emotions in the text (positive, negative, anger, anticipation, disgust, fear, joy, sadness, trust); the proportion of words that involved scarcity; and the proportion of color in the letter (hot/cold). The variables were standardized so that differences within the variables and between clusters would be easier to interpret.

Three separate methods were used to determine the optimal number of clusters: the elbow method, the silhouette method, and the gap-statistic method.[1] The plots output from each method suggested that the silhouette method recommended two, the gap-statistic method two to four, and the elbow method four. Four clusters were selected to better explore a greater number of different aspects of the fraud letters. If the four clusters were found to be meaningful and different, examining how those differences influenced susceptibility would have ecological importance.

Results

The clusters

All the analyses were conducted using R with the factor extra, cluster, and magrittr packages. Overall, the data were 'clusterable' according to the Hopkins statistic. A Hopkins statistic near 0 represents a clusterable data set, whereas a value near 1 represents a data set that is uniform and less clusterable. The Hopkins statistic for the variables was .15, representing data that were clusterable. *K*-means clustering was used to separate the data into four separate clusters. *K*-means clustering is used to assign each input variable to one of the *K* groups, *K* being the number of specified clusters chosen (Trevino, 2016). This process involved examining the cluster descriptions (see Table 1), which display the *g* values where the centroid of each cluster rested on each attribute. Examining the clusters' most prominent attributes allowed the general theme of the letter to stand out and be compared to common scams that are received in the mail. Below are the clusters obtained from the data. A prototypical letter from each cluster can be found in Appendix A.

Table 1. Cluster centroids.

Cluster	Reward	Multi-Prize	Mention	Activation	Scarcity	Word Count	Color		
1	0.01	−0.36	−0.03	0.02	0.15	0.04	−0.18		
2	−0.08	−0.19	0.27	−0.02	0.29	−0.11	0.17		
3	0.33	1.65	0.29	−0.41	−0.16	0	0.61		
4	−0.13	−0.29	−0.6	0.16	−0.16	0.08	−0.14		
Cluster	POS	NEG	ANGER	ANTICIP	DISGUST	FEAR	JOY	SAD	TRUST
1	−0.09	0.34	0.16	0.02	0.6	0.2	−0.05	0.67	0
2	1.22	0.52	1.73	1.57	0.13	1.82	1.87	0.45	1.28
3	0.42	0.09	−0.13	0.24	−0.16	−0.25	0.12	−0.05	0.25
4	−0.49	−0.53	−0.65	−0.64	−0.53	−0.67	−0.61	−0.75	−0.51

Cluster 1: negative-cold, one-reward letters

Cluster 1 contained 75 letters. These letters characteristically featured one prize and contained an above-average amount of negative emotion, specifically disgust, fear, and sadness. The letters were also typically low in color and contained text that highlighted the scarcity of the prize. After viewing the cluster and some prototypical letters we saw that these letters highlighted the fear aspect of missing out on the prize, and the sadness aspect came from the letter describing the feeling of not wanting to miss out. Additionally, they were usually on white paper with black text and appeared very formal.

Cluster 2: high emotionality, high scarcity letters where a prize is mentioned often

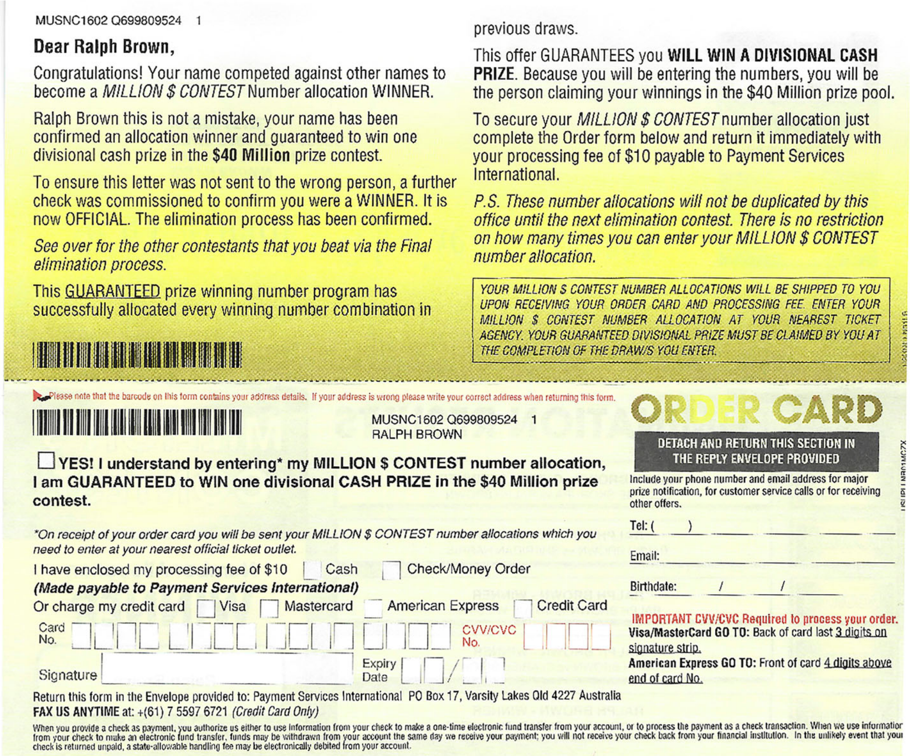
Cluster 2 contained 26 letters. These letters were characteristically filled with the highest emotion of any of the clusters, except for disgust, fear, and sadness (see cluster 1). Other attributes of this cluster were that the reward was mentioned often, and the text contained the highest number of words highlighting the scarcity of the prize offering. Appeal to emotion is a common persuasion tactic (Cialdini, 2007); therefore, it makes sense that one of the clusters of letters would be defined by their highly emotional content.

Cluster 3: very colorful multi-prize letters (sweepstakes)

Cluster 3 contained 34 letters. These letters typically mentioned many rewards but also had a much higher reward amount and the rate at which a reward was mentioned than the other clusters. Letters in this cluster were also typically the most colorful and had the lowest activation amount of any cluster. They were fairly neutral when it came to emotion. This cluster was also expected; one of the most common fraud gambits is the sweepstake, where there are multiple awards that 'you may have already won.' (For an example of a letter, see Figure 1).

Cluster 4: low emotionality, low scarcity, cold letters

Cluster 4 contained 80 letters. These letters were typically low in emotionality and scarcity claims. The typical letter in this cluster also had the lowest reward and was deemed to be cold in nature. While not picked up in the cluster analysis, it was assumed that these



MUSNC1602 Q699809524 1

Dear Ralph Brown,

Congratulations! Your name competed against other names to become a *MILLION $ CONTEST* Number allocation WINNER.

Ralph Brown this is not a mistake, your name has been confirmed an allocation winner and guaranteed to win one divisional cash prize in the **$40 Million** prize contest.

To ensure this letter was not sent to the wrong person, a further check was commissioned to confirm you were a WINNER. It is now OFFICIAL. The elimination process has been confirmed.

See over for the other contestants that you beat via the Final elimination process.

This GUARANTEED prize winning number program has successfully allocated every winning number combination in previous draws.

This offer GUARANTEES you **WILL WIN A DIVISIONAL CASH PRIZE**. Because you will be entering the numbers, you will be the person claiming your winnings in the $40 Million prize pool.

To secure your *MILLION $ CONTEST* number allocation just complete the Order form below and return it immediately with your processing fee of $10 payable to Payment Services International.

P.S. These number allocations will not be duplicated by this office until the next elimination contest. There is no restriction on how many times you can enter your MILLION $ CONTEST number allocation.

YOUR MILLION $ CONTEST NUMBER ALLOCATIONS WILL BE SHIPPED TO YOU UPON RECEIVING YOUR ORDER CARD AND PROCESSING FEE. ENTER YOUR MILLION $ CONTEST NUMBER ALLOCATION AT YOUR NEAREST TICKET AGENCY. YOUR GUARANTEED DIVISIONAL PRIZE MUST BE CLAIMED BY YOU AT THE COMPLETION OF THE DRAW/S YOU ENTER.

Please note that the barcode on this form contains your address details. If your address is wrong please write your correct address when returning this form.

MUSNC1602 Q699809524 1
RALPH BROWN

ORDER CARD

DETACH AND RETURN THIS SECTION IN THE REPLY ENVELOPE PROVIDED

Include your phone number and email address for major prize notification, for customer service calls or for receiving other offers.

Tel: ( )

Email:

Birthdate: / /

☐ **YES! I understand by entering* my MILLION $ CONTEST number allocation, I am GUARANTEED to WIN one divisional CASH PRIZE in the $40 Million prize contest.**

**On receipt of your order card you will be sent your MILLION $ CONTEST number allocations which you need to enter at your nearest official ticket outlet.*

I have enclosed my processing fee of $10 ☐ Cash ☐ Check/Money Order
(Made payable to Payment Services International)

Or charge my credit card ☐ Visa ☐ Mastercard ☐ American Express ☐ Credit Card

Card No. CVV/CVC No.

Signature Expiry Date /

IMPORTANT CVV/CVC Required to process your order.
Visa/MasterCard GO TO: Back of card last 3 digits on signature strip.
American Express GO TO: Front of card 4 digits above end of card No.

Return this form in the Envelope provided to: Payment Services International PO Box 17, Varsity Lakes Qld 4227 Australia
FAX US ANYTIME at: +(61) 7 5597 6721 *(Credit Card Only)*

When you provide a check as payment, you authorize us either to use information from your check to make a one-time electronic fund transfer from your account, or to process the payment as a check transaction. When we use informatior from your check to make an electronic fund transfer, funds may be withdrawn from your account the same day we receive your payment; you will not receive your check back from your financial institution. In the unlikely event that your check is returned unpaid, a state-allowable handling fee may be electronically debited from your account.

Figure 1. An example of a letter form Cluster 3.

letters would appear to be more businesslike and contain more authority, such as purportedly originating from a government agency or well-known organization.

Discussion

Mass marketing solicitations come in many different forms and contain different types of content. Using cluster analysis, we were able to identify four distinct types of MMSs. Each cluster was characterized by unique features. Taken together, the results demonstrate that scammers tend to utilize a range of techniques and manipulations to get individuals to respond to their scams. While contributing insight about MMS designs and features is of key importance, our analysis falls short of providing knowledge about which technique is most successful in eliciting consumers responses. That is, we do not know which cluster (type of letter) tends to elicit the highest compliance rate. Given that each type of solicitation utilizes different features, the next logical step is to experimentally test which of the four clusters of MMS letters is most likely to lead to compliance or responding to the letter. Furthermore, previous work (Wood et al., 2018) has shown that higher benefit perception and lower risk perception was associated with higher intention to respond to the MMS. Therefore, in experiment 2, in addition to evaluating intention to comply/reply, we were also interested in evaluating the impact of each type of letter on participants' perceptions of benefits and risks.

Experiment 2: administration of letters to consumers to assess response to clusters

Overview

In this experiment, one prototypical letter (as discussed above) from each of the four clusters was modified to protect the identity of the original victim so it could be presented to participants anonymously. The letters differed according to the attributes of the clusters (e.g. monetary prize size).

We first examined the overall effects and then the effects for each letter. While effects across letters were examined, interpreting the results is not necessarily straightforward. The letters differed in reward amount and activation amount, variables that could influence participants' willingness to comply. Therefore, the analyses instead aimed to determine if there were differences within each of the clusters that do not appear when examining the effect overall (across all clusters). A combination of Wilcoxon rank tests, Kruskal–Wallis tests, and comparison of effect sizes in regression analyses were used to make insights.

Method

Participants

Three hundred thirty-five adults were recruited on MTurk. Fifty-one respondents were excluded because they failed the manipulation check, completed the survey in an unreasonably short time, or failed to complete sections of the study materials (for demographics, see Table 2). Thus, the final sample consisted of 281 adults ranging in age from 21 to 81 years ($M = 54.5$ years, SD = 17.15). All participants were residents of the United States.

Materials

Participants were randomly assigned to view one of the four MMS solicitation letters that were identified in the study 1 cluster analysis (see Appendix A).

Need for Cognition scale (Cacioppo et al., 1984). The NFC is an 18-item questionnaire that evaluates the degree to which people engage with and enjoy cognitively demanding activities (e.g. 'I prefer complex to simple problems' and 'I prefer my life to be filled with puzzles I must solve'; Cacioppo et al., 1984). Participants were asked to indicate on a scale from 1 (extremely uncharacteristic of me) to 5 (extremely characteristic of me) whether or not the statement is characteristic of themselves. The Cronbach's α for this scale for this sample was 0.96418, which indicates that the items are assessing the same construct.

Intention to respond: Participants were asked to rate their interest in the letter and how likely they were to send in the activation fee on a Likert scale ranging from 1 (*extremely unlikely*) to 7 (*extremely likely*).

Perception of benefits and risks: Participants were also asked to provide two qualitative statements about the benefits and risks of sending in the activation fee as well as to fill out the. Quantitative rankings were also collected, on a scale of 1 (*no benefit/risk*) to 7

Table 2. Demographics.

Variable	Older adults (*n* = 158)	Younger adults (*n* = 123)
Age (*M*, SD)	68.02 (3.91)	36.90 (10.26)
Gender		
Male (*n*, %)	62 (39.24%)	63 (51.22%)
Female (*n*, %)	96 (60.76%)	59 (47.97%)
Other (*n*, %)	0 (0%)	1 (0.81%)
Ethnicity		
White (*n*, %)	147 (93.04%)	85 (69.11%)
American Indian/Alaska Native (*n*, %)	0 (0%)	1 (0.81%)
Asian/Pacific Islander (*n*, %)	0 (0%)	11 (8.94%)
Black (*n*, %)	9 (5.70%)	11 (8.94%)
Hispanic (*n*, %)	0 (0%)	10 (8.13%)
Other (*n*, %)	2 (1.27%)	1 (0.81%)
More than one (*n*, %)	0 (0%)	4 (3.24%)
Income (yearly)		
$0–$24,999 (*n*, %)	55 (34.81%)	28 (22.76%)
$25,000–$49,999 (*n*, %)	55 (34.81%)	41 (33.33%)
$50,000–$74,999 (*n*, %)	27 (17.09%)	34 (27.64%)
$75,000–$124,999 (*n*, %)	17 (10.76%)	13 (10.57%)
$125,000–$174,999 (*n*, %)	2 (1.27%)	4 (3.25%)
$175,000+ (*n*, %)	2 (1.27%)	3 (2.44%)
Education		
Less than GED (*n*, %)	1 (0.633%)	0 (0%)
High school/GED (*n*, %)	36 (22.78%)	30 (24.39%)
Associate's degree (*n*, %)	34 (21.52%)	23 (18.70%)
Bachelor's degree (*n*, %)	50 (31.65%)	53 (43.09%)
Master's degree (*n*, %)	27 (17.09%)	14 (11.38%)
Professional degree (*n*, %)	3 (1.90%)	3 (2.439%)
Ph.D. (*n*, %)	7 (4.43%)	0 (0%)
Employment		
Full time (*n*, %)	27 (17.09%)	88 (71.55%)
Part time (*n*, %)	40 (25.32%)	24 (19.51%)
Unemployed (*n*, %)	91 (57.59%)	9 (7.32%)
Student (*n*, %)	0 (0%)	2 (1.63%)
Marital status		
Single (*n*, %)	29 (18.35%)	62 (50.41%)
Married (*n*, %)	73 (46.20%)	55 (44.72%)
Divorced (*n*, %)	42 (26.58%)	6 (4.88%)
Widowed (*n*, %)	14 (8.86%)	0 (0%)

Note. GED = General education diploma; NFC = Need for Cognition scale.

(*high benefit/risk*). Demographics (age, gender, ethnicity, income, education, employment, and marital status) were collected at the end of the survey. A manipulation check was also included at the end of the survey asking participants to write the activation amount for the prize in the letter.

Procedures

Previous research has shown that MTurk participants are reliable and results are similar to those obtained by using hand-completed surveys (Casler et al., 2013). After selecting the study on MTurk, participants were redirected to a Qualtrics site and were asked to read through a consent form. Those who agreed to the terms and consented were randomly assigned to one of the four solicitations. They then completed the NFC scale. At the end of the study, participants were debriefed, informed of the goal of the study, and paid $1.50 for their participation.

Results

Overall, 13% of the sample indicated some interest in the letters, but only 2% indicated an intention to send in the activation fee. Respondents were classified as being interested if they selected *somewhat interested* (5) through *extremely interested* (7) on the 1–7 scale measuring interest (see Wood et al., 2018). Likewise, respondents were classified as intending to send in an activation fee if they responded being *somewhat likely* (5) through *extremely likely* (7) on the 1–7 scale measuring intention. Of those who indicated some interest in the letter, 18% intended to respond to the letter. Additionally, almost all those who intended to mail in the activation fee were interested in the letters (88%); the other 12% responded that they were neither interested nor disinterested.

Because of the low number of participants who indicated an intention to respond, we examined intention to respond when possible but also included interest as another measure of susceptibility, under the assumption that those who are interested are more likely to send in an activation fee. A Wilcoxon rank sum test with a continuity correction confirmed that those who responded had significantly higher interest scores ($Z = -5.41$, $df = 283$, $p < .001$). Additionally, turning interest and likelihood into dichotomous variables (1–3 no interest/would not respond, 5–7 interest/would respond) allowed us to input them in a chi-square test of independence. The chi-square test showed that responding was dependent on being interested in the prize offer ($\chi^2(1)$ 34.84, $p < .001$), further supporting extrapolating likelihood from interest.

Violations of normality were common, owing to the nature of our variables (most people did not want to respond). Because of this, nonparametric tests were run when necessary. Overall, a Kruskal–Wallis test revealed that intention to send in the activation fee was not significantly different depending on the letter cluster ($\chi^2(3)$ 5.17, $p = .16$); interest in the prize amount was also not significantly different depending on the letter cluster ($\chi^2(3)$ 3.80, $p = .28$). Additionally, the letter cluster did not differ by the ranking of how beneficial ($\chi^2(3)$ 2.78, $p = .427$) or risky ($\chi^2(3)$ 7.40, $p = .06$) they were perceived to be. However, when interest was dichotomized into interested or not interested, a chi-square test revealed that interest was dependent on which letter cluster participants read ($\chi^2(3)$ 9.50, $p = .02$). Chi-square post hoc comparisons using the Bonferroni correction revealed that the only significant difference between conditions among those interested versus not interested was between cluster 2 (interested = 4, not interested = 65) and cluster 4 (interested = 16, not interested = 65; $p_{\text{adjusted}} = .04$). The post hoc comparisons used the Bonferroni correction to avoid Type 1 error with the multiple comparisons, resulting in an adjusted *p*-value. The last result suggests that there may be response/interest differences among the clusters.

Interestingly, there was an age difference such that younger individuals indicated higher interest in the prize option ($Z = 4.44$, $df = 283$, $p < .001$) and expressed higher intention to send in the fee ($Z = 3.16$, $df = 283$, $p = .001$) than did older adults. Additionally, younger adults rated the letter as significantly more beneficial ($M = 1.9$, SD = 1.73) and less risky ($M = 6.47$, SD = 1.28) than older adults ($M_{\text{benefit}} = 1.31$, SD = 1.08; $M_{\text{risk}} = 6.86$, SD = 0.51; $Z_{\text{benefit}} = 3.49$, $p < .001$; $Z_{\text{risk}} = -3.14$, $p < .01$). Those who reported having previously seen a letter similar to the one they viewed in this study were less likely to be willing to send in a fee for the prize ($Z = 3.79$, $df = 283$, $p < .001$) and were less interested than those who had not seen a similar letter in the past ($Z = 4.51$, $df = 283$, $p < .001$).

A stepwise multiple linear regression revealed that the intention to send in a fee was predicted by participants' ratings of the benefit ($B = .82$) and riskiness ($B = -.25$) of the letter ($F(2, 272)$ 161.6, $p < .001$, $R^2 = .54$), replicating past research. In a second step, NFC score and age were added to the model. Age ($B = -.009$) was a significant predictor along with benefit ($B = .78$) and riskiness ($B = -.23$) but NFC score was not significant ($F(4, 260)$ 77.69, $p < .001$, $R^2 = .54$).

Cluster 1: negative-cold, one-reward letters

Of those who saw the letter from cluster 1, 11% indicated they were interested in the prize option, selecting somewhat interested (5) through extremely interested (7) on the 1–7 scale measuring interest, while 3% indicated an intention to send in the activation fee, responding being somewhat likely (5) through extremely likely (7) on the 1–7 scale measuring intention. Intention to send in a fee differed by age, with younger adults ($M = 1.65$, SD = 1.33) expressing greater intention than older adults ($M = 1.16$, SD = 0.81) to send in the fee ($Z = 2.56$, $p = .01$). Younger adults ($M = 2.26$, SD = 1.93) were also significantly more interested in the prize option than older adults ($M = 1.53$, SD = 1.24; $Z = 2.35$, $p = .018$). Neither likelihood of sending in the fee ($F(1, 68)$ 1.29, $p = .28$) nor interest in the prize ($F(1, 68)$ 1.99, $p = .16$) was predicted by NFC score. When examining how beneficial the offer appeared to be, there was no difference between younger ($M = 1.93$, SD = 1.78) and older ($M = 1.31$, SD = 1.2) adults ($Z = 1.92$, $p = .055$). When examining how risky the offer in the letter appeared to be, younger adults ($M = 6.06$, SD = 1.75) viewed the letter as significantly less risky than older adults ($M = 6.93$, SD = 0.34; $Z = -3.40$, $p < .001$).

Stepwise multiple linear regression indicated that likelihood of sending in the activation fee was significantly predicted by age ($B = -.01$; $F(1, 72)$ 5.39, $R^2 = .06$, $p = .02$) such that younger adults were more likely to send in an activation fee than older adults. However, when participants' ratings of benefit ($B = .39$) and risk ($B = -.22$) were added to the model in the second step, age was no longer a significant predictor while the model was still significant ($F(3, 67)$ 29.47, $R^2 = .55$, $p < .001$). No other differences were found for cluster 1.

Cluster 2: high emotionality, high scarcity letters where prize is mentioned often

Of those who saw the letter from cluster 2, 6% indicated they were interested in the prize option, selecting somewhat interested (5) through extremely interested (7) on the 1–7 scale measuring interest, while 0% indicated being likely to send in the activation fee, responding being somewhat likely (5) through extremely likely (7) on the 1–7 scale measuring intention. Likelihood of sending in the fee did not differ between younger ($M = 1.84$, SD = 1.79) and older ($M = 1.21$, SD = 0.62) adults ($Z = 1.69$, $p = .09$). Neither likelihood of sending in the fee ($F(1, 63)$ .14, $p = .71$) nor interest in the prize ($F(1, 64)$ 3.96, $p = .051$) was predicted by NFC score. When examining how beneficial the offer appeared to be, there was no difference between younger ($M = 1.47$, SD = 1.33) and older ($M = 1.26$, SD = 1.08) adults ($Z = 1.08$, $p = .28$). When examining how risky the offer in the letter appeared to be, there were no differences between younger ($M = 6.84$, SD = 0.64) and older ($M = 6.84$, SD = 0.06) adults ($Z = .23$ $p = .81$).

Stepwise multiple linear regression indicated that tikelihood of sending in the activation fee was not significantly predicted by age (F(1, 66) 5.39, $R^2 = .00$, $p = .33$). When benefit ($B = .09$, $p = .04$) and risk ($B = -.16$, $p = .054$) were added to the model in a second step, benefit was the only significant predictor (F(3, 62) 3.27, $R^2 = .09$, $p = .027$). No other differences were found for the cluster.

Cluster 3: very colorful multi-prize letters (Sweepstakes)

Of those who saw the letter from cluster 3, 11% indicated they were interested in the prize option while 2% indicated a likelihood of sending in the activation fee. Likelihood of sending in the fee did not differ for younger ($M = 1.45$, SD = 0.99) and older ($M = 1.09$, SD = 0.28) adults ($Z = 1.69$, $p = .09$). However, interest in the prize was significantly greater for younger ($M = 2.19$, SD = 2.01) compared to older ($M = 1.24$, SD = 0.78) adults ($Z = 2.34$, $p = .017$). Neither likelihood of sending in the fee (F(1, 62) 1.04, $p = .31$) nor interest in the prize (F(1, 61) .38, $p = .53$) was predicted by NFC score. When examining how beneficial the offer appeared to be, there was no difference between younger ($M = 1.68$, SD = 1.42) and older ($M = 1.43$, SD = 1.22) adults ($Z = .87$, $p = .38$). When examining how risky the offer in the letter appeared to be, there was no difference between younger ($M = 6.71$, SD = 1.13) and older ($M = 6.89$, SD = 0.4) adults ($Z = -.21$, $p = .84$).

Stepwise multiple linear regression indicated that likelihood of sending in the activation fee was significantly predicted by age (F(1, 64) 7.93, $R^2 = .09$, $p = .006$) Additionally, when benefit ($B = .25$, $p < .001$) and risk ($B = -.29$, $p < .001$) were added to the model with age ($B = -.01$, $p < .01$) in a second step, the model predicted significantly more than age alone (F(3, 62) 27, $R^2 = .54$, $p < .001$). No other differences were found for the cluster.

Cluster 4: low emotionality, low scarcity cold letters

Of those who saw the letter from cluster 4, 22% indicated they were interested in the prize option while 6% indicated a likelihood of sending in the activation fee. Likelihood of sending in the fee did not differ for younger ($M = 1.93$, SD = 1.62) and older ($M = 1.32$, SD = 0.96) adults ($Z = 1.94$, $p = .051$). However, interest in the prize was significantly higher for younger ($M = 2.87$, SD = 2.47) compared to older ($M = 1.79$, SD = 1.84) adults ($Z = 2.43$, $p = .015$). Neither likelihood of sending in the fee (F(1, 67) .73, $p = .39$) nor interest in the prize (F(1, 68) .45, $p = .50$) was predicted by NFC score. When examining how beneficial the offer appeared to be, younger adults ($M = 2.53$, SD = 2.18) gave significantly higher beneficial scores than older adults ($M = 1.24$, SD = 0.82; $Z = 2.99$, $p = .002$). When examining how risky the offer appeared to be, younger adults ($M = 6.27$, SD = 1.23) viewed the letter as being significantly less risky than older adults ($M = 6.79$, SD = 0.65; $Z = -2.25$, $p = .02$).

Stepwise multiple linear regression indicated that likelihood of sending in the activation fee was significantly predicted by age (F(1, 69) 5.40, $R^2 = .05$, $p = .02$). Additionally, the model was still significant when benefit ($B = .36$, $p < .001$) and risk ($B = -.71$, $p < .001$) were added to the model with age ($B = .01$, $p = .035$; F(3, 67) 71.81, $R^2 = .75$, $p < .001$) in the second step, and that model predicted significantly more than age alone (F(23, 67) 97.46, $p < .001$). No other differences were found for the cluster.

Discussion

Financial fraud not only inflicts monetary pain but can affect a person's psychological and physical health and well-being (Button et al. 2014; DeLiema et al., 2017). It is little wonder that law enforcement agencies across the globe have issued warnings, and like the FBI, and have tried to identify fraud themes in their constant attempt to reduce the number of victims. In this study we were inspired to apply Simon's (1990) argument – that to better understand the human decision-making process one must understand both the person and the environment in which that person operates – to the problem. To do so, we first used cluster analysis to capture the different facets of various MMS solicitations. In other words, we identified the different decision environments that are created by fraudsters and faced by individuals. Next, we conducted an experiment to evaluate how different clusters (impact the decision maker's intention to respond to these solicitations.

Our cluster analysis – a method previously used in various academic fields to organize data – revealed the diversity of MMSs used by scammers. Fraudsters employ different presentation techniques in their efforts to get a response from individuals. That is, they are creating different environmental structures to lure potential victims. Their techniques can be grouped into four distinct clusters. In some cases (cluster 1), their scam letters highlight a single high-value prize as well as focusing on negative emotions. Letters in cluster 2, in contrast, mentioned the prize money several times and were saturated with emotional terminology as well as highlighting the scarcity of the offer. In cluster 3, in contrast, the letters were very colorful, and a high reward was a key feature. Last, letters in cluster 4 largely failed to induce a sense of scarcity or emotionality and contained a small reward. Our work extends earlier research using content analysis to capture fraud in organizations' reports (Churyk et al., 2008) or in MMSs (Chang, 2008; see also Sabau, 2012). Indeed, whereas Chang's (2008) analysis contained only six cases of an MMS (compared to 215 in our study), both studies identified scarcity and emotionality as key tactics used by MMSs. Corresponding almost perfectly with Cialdini's work on persuasion, Fischer et al. (2013) identified emotional cues, trust and authority cues, cost–benefit considerations (size of the prize), behavioral commitments, and sunk–cost considerations as factors manipulate by fraudsters. The present work, similarly, found that emotional cues, authority, and prize size were some of the key factors manipulated by fraudsters to manufacture different types of MMS. There is convergence evidence, therefore, that fraudsters tend to create several distinct fraudulent solicitations (or decision environments) in their efforts to garner response.

Drawing on Simon's (1956) intuition and Cialdini's work about principles of persuasion (2007), cluster analysis allowed us to explore one blade of Simon's scissors (namely, the structure of the environment). Indeed, both researchers argue that different environmental conditions or structures can impact decision making. While Simon was focusing on statistical structures (e.g. food distribution in the environment), Cialdini's advocates the presence (or absence) of factors such as scarcity and authority. Thus, a key question is how different clusters impact individuals' intention to comply. Does the presence or absence of key features – such as scarcity, authority, and emotional reference – increase or decreases the intention to comply with scammer solicitations?

Our results from the cluster comparison did reveal suggestive differences among the clusters in terms of interest in the solicitation and intention to send in the activation fee. For example, while 22% of those who saw a letter from cluster 4 expressed interest, only 6% of those who saw a letter from cluster 2 did so. When focusing on intention to send in the activation fee, our data reveal that 0% of those who viewed a cluster-2-type letter expressed intention to reply or send in the activation fee, while 6% of those who viewed a letter categorized as cluster 4 expressed an intention to do so. Our results, thus, indicate that individuals are significantly more likely to respond to some types of MMSs over others.

Interestingly, despite these differences, participants rated the four types of letters as equally beneficial and risky. The present results are also reminiscent of earlier findings by Wood et al. (2018), who experimentally varied the amount of a prize (small vs. big) and source of the solicitation (known vs. unknown company) but found little to no variation in participants' intention to comply with the solicitation. It seems, thus, that evaluation of benefits and risks are not driven by any specific feature of the sonication, even when letters contained emotional cues, scarcity of large amount of prize. These findings are consistent with earlier work by Fischer et al. (2013) and Wood et al. (2018) who reported no differences in intention to respond to different fraud solicitations. Surprisingly, thus, the notion that different environmental structures would impact the decision making does not seems to apply to MMS. Indeed, the presence or absence of some of the principles advocated by Cialdini – such as scarcity or authority – made little difference in individuals' intention to respond to the solicitation. These findings highlight the need to further examine what factors impact individuals' tendency to respond to scam solicitations (see Hanoch & Wood, 2021)

Importantly, our second study found an overall age effect, with younger adults expressing greater interest and intention to comply compared to older adults. Younger adults, furthermore, tended to view some letters (clusters 1 and 4) as significantly less risky (but not more beneficial) compared to the older adults. These results are consistent with emerging literature showing (somewhat counterintuitively) that older adults might not be more vulnerable to fraud compared to their younger counterparts (Mueller et al., 2020; Thompson, 2017). Older adults may be simply targeted more often, as they tend to have more assets (see Sawhill & Pulliam, 2019) and lose a greater amount of money to fraud (Thompson, 2017). This study did not include older adults with cognitive impairment or dementia, who may have greatly increased susceptibility.

Previous work (Mueller et al., 2020; Wood et al., 2018) has likewise identified perceptions of benefits and risks as key predictors in individuals' responses to a fraudulent solicitation. The present experiment lends further support to this growing body of work, as in all four clusters, participants' perception of the benefits and risks were significant predictors of both interests in the solicitation and intention to send in the activation fee. Given the consistent findings in this area, one clear recommendation is to increase consumers' risk perception while reducing their perception of the benefits. Further research is urgently needed to pinpoint the precise mechanism that would achieve this goal.

Using cluster analysis in the realm of fraud could have clear legal implications. Work by Lippert and Golding (2016) have found that mock jurors were more likely to hand a pro-victim verdict when an older person testified for an older victim compare to when a younger person testified, or no witness was present. In a related study, Riederer and

Golding (2020) examined perception of plea bargains in elder financial abuse cases. In this study, they manipulated the amount of money ($5 K vs $50 K), relationship to the victim (son vs. caretaker), and type of sentence (reduce jail vs. probation). Their data revealed that a plea bargain was the preferred choice in cases when the sum was lower, sentence was more severe (a reduced jail sentence), and when the preparator had a closer tie to the victim (a son). Similar work is urgently needed to examine how different information containing in MMS might impact jurors' perception of guilt and verdicts.

A strength of the present experiment is the use of a large number of real mass marketing solicitations, but the experiment is not without limitations. First, the experiment focused only on MMSs and it is unclear whether our results are robust enough to be applicable to other types of fraud. Furthermore, the experiment is hypothetical by nature. For obvious ethical reasons, it is largely impossible to conduct a study that actively defrauds participants. That being said, our results, at least with regard to participants' interest, largely mirror the rate of fraud victimhood reported in the literature (about 1 in 10) (see Anderson, 2019).

A second limitation of the present study rest with the hypothetical nature of the task. In experiment 2, participants were asked to indicate their intention and perception of the MMS. They were not asked to provide actual response. Hanoch and Wood (2021) have argued that more realistic, ecologically valid studies are required to improve the external validity work in the field and on the need develop means to conduct natural field studies. Work by Ebner et al. (2018) can serve as inspiration, although ethical and technical issues render such studies challenging.

The present line of work could also help inspire future research. Romance scam is one prime example where cluster analysis could help identify themes and ideas that could help individuals avert fraudulent advertisements. Much of the literature thus far has focused on profiling the victims (e.g. Buchanan & Whitty, 2011), and less efforts have been devoted to exploring the type of language and cues used by romance fraudsters. Likewise, the methodology employed in the present paper could easily be extended to study a range of other types of scams (Covid-19, cryptocurrencies, travel, etc.) and help shed light on the techniques and language used by scammer. It could also help generate new preventive measures, though further studies would need to examine this important, and very much under studied, domain.

Simon's influential work paved the way for many novel and important insight in the field of judgment and decision making. To date, we are not aware of other studies that have applied his insight to the investigation of mass marketing fraud. Our novel approach provides several key insights that could help the FBI and other law enforcement agencies across the globe better hone their advice. We find that not all mass marketing solicitations are alike and that fraudsters use different persuasion techniques to elicit compliance. They vary the prize amount, the scarcity, and the emotional tone of the letters, very much along the lines of Cialdini's principles of persuasion (Cialdini, 2007). Using cluster analysis to reveal these underlying mechanisms was only the first step, however. Our investigation has also shown that different solicitations might generate different levels of interest and compliance, as well as differences in benefit and risk perceptions. Our work, thus, provides not only a more comprehensive theoretical insight into the workings of MMSs but also practical tools that could potentially aid those trying to mitigate and fight fraud.

Data from this study is available upon request.

Note

1. A more in-depth explanation of these techniques goes beyond the scope of the paper (see, https://www.datanovia.com/en/lessons/determining-the-optimal-number-of-clusters-3-must-know-methods/). However, it is important to note that there are no objective methods to determine the optimal number of clusters. Thus, in this study we employed three different common techniques. We have opted to for a conservative approach, and hence used four cluster rather than two.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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