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Research

Influence of emoticons on deception detection: An empirical exploration

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A R T I C L E I N F O

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A B S T R A C T

Text messages with strategically placed emoticons impact recipient perceptions regarding truth or deception of the content. This article describes an experiment using 3 treatments applied randomly to 4 deceptive and 4 truthful message snippets. The original content of the snippets related to scholarship interviewee comments that truthfully or deceptively described their background. Each message was represented in one of three ways: plain text, annotated text, or text with embedded emoticons. The data were analyzed using a 2 (Text Veracity: Honest or Dishonest) x 3 (Cues: Plain Text vs Annotated Text vs Emoticons) design. The dependent variable reflected participant perception of the snippet's honesty or dishonesty. Results show extra emotional cues impacted perceptions of the message content. Overall, this study demonstrated annotated text and text with embedded emotion were more likely to be judged as deceptive than plain text. This was particularly true when messages were deceptive. True messages were detected as truthful more often in plain text.

1. Introduction

Deception is an unfortunate but common occurrence in many computer mediated communication venues [34,42]. Lean computer media, characterized by reduced capacity to carry information, is no exception. Modern applications such as email, social media posts, and text messages fall into this category. According to the Pew Research Center [45], 78% of females and 65% of males in the U.S. regularly used social media. While popular, using leaner, computer-based exchanges can make discerning non-verbal cues a difficult and cognitively taxing challenge [8,51]. Various approaches have evolved in an attempt to use nonverbal cues that can enhance communication in these venues [5,36]. Included are: (1) replacement of physical gestures with symbols (e.g., emoticons or icons like a thumbs-up or smiling face) [17]; and (2) addition of annotated text or paralanguage (e.g., descriptors that provide details about the message sender's emotional or physical state) [30,39]. Despite widespread use, nonverbal cues embedded in both speech and text can be non-diagnostic [2] and easily misunderstood [27,61]. Regardless of interpretation of the message, these cues impact perceptions.

1.1. Emoticons

Emoticons are graphical representations of facial expressions or body positions meant to convey the sender's emotional state or provide other nonverbal cues [17]. Emoticons often are used in lean communication applications which are increasingly popular due to availability, ease of use, and low cost [52]; and because of widespread mobile technology [28]. Huang et al. [29] report that use of emoticons supplement nonverbal communication and add to feelings of enjoyment, personal interaction, perceived information richness, and perceived usefulness; and therefore add to communication value. In lean communication channels, researchers suggest that emoticons act as nonverbal surrogates [15] and enhance the exchange of social information [55] when used in purposeful ways [48]. In some instances, this is an advantage since the risk of unintentionally leaking nonverbal information is lower in lean venues [40]. As suggested by Derks et al. [[14], p. 380], "[*e*]moticons are used more consciously than actual nonverbal behavior, which implies that there is more control over the message a person wants to convey." Therefore, emoticons allow a sender to influence the receivers' perceptions of message intention [46]. While this can clarify and enhance message content, it also can encourage deception. This perspective is supported by Luor et al. [37] who suggest that "IM text messages containing emoticons [generate] different emotional effects compared with those without emoticons in some scenarios. Therefore, emoticons may serve the function of modified text messages." In the current study, we expect to find that people interpret messages differently when texts are infused with additional social meaning through use of emoticons [14,15,63] This idea is examined in Hypothesis 1:

H1: People's perceptions are altered by emoticons or other cues in lean media.

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1.2. Deception in lean media

Deception in communication has been defined as "a message knowingly transmitted by a sender to foster a false belief or conclusion by the receiver" ([4], p. 205). This definition suggests deception is intentional, means to mislead or create a false perception in a recipient, and excludes mistakes and/or non-intentional behaviors. Under this definition, it stands to reason that deceptive communication takes longer to formulate [41] and could lead to inconsistencies [62], particularly in synchronous settings. Past research into face-to-face communication suggests unintentional signals called leakage provide indicators of deception [13,51]. A strategically dishonest sender can avoid use of known deception indicators to thwart detection and, as such, enshroud the truth [23,24,57,58]. Derks et al. [14] suggest richer lean media such as emoticons can be used for this purpose.

1.2.1. Plain text

Lean media is common in modern computer mediated communication systems and is characterized by a low capacity to carry information compared to face-to-face interaction or other richer forms of communication [9,10]. Since plain text is a less-rich media, deception may be more difficult to detect [22] when messages are sent in this form. Prior studies indicate that plain text alone may not be enough to reliably detect deception [39], although attempts to automate deception detection indicate sophisticated algorithms may one day improve the situation [57,59]. Hypothesis 2 addresses deception detection with plain text to establish a baseline within the current dataset:

H2: People are less likely to detect deception in plain text due to a dearth of emotional and non-verbal cues.

1.2.2. Enriching plain text

Plain text can be enhanced or annotated with non-verbal cues, such as hand gestures, smiles, frowns, yawns, or other words to indicate emotional content. Some researchers describe this as paralanguage [30,36]. Annotating plain text with additional text descriptors should enhance a message's capability to transmit more meaning or sentiment [54], and this may lead to more successful deception detection [47]. We believe annotated text can introduce higher levels of media richness [12]. This leads to our third hypothesis:

H3: People are more likely to detect deception in annotated text messages than plain text since the number of cues is enhanced.

Emoticons also can provide a mechanism to enrich lean media [53]. The use of emoticons enhances communication with additional information in ways that approximate how non-verbal communications enhance face-to-face communication [29]. Therefore, we believe the enhancement of media richness will result in higher levels of deception detection. Our Hypothesis 4 becomes:

H4: People are more likely to detect deception in messages that contain emoticons than plain text since the number of cues is enhanced.

1.3. Deception in social media type communications

Many receivers believe that online communication, particularly from unknown persons, can be deceptive [16,25]. Other researchers support this viewpoint from a variety of perspectives [49,60]. Brennen [3] looked at underlying motivations for online deception and suggested that, "[*l*]ies affect the distribution of power in society. Lies add to the power of the liar and reduce the power of those who have been deceived by altering their choices. Lies may misinform us by eliminating some of our objectives or making certain objectives seem unattainable or no longer desirable" [3].

Since people already appear to distrust social media [64], we believe that people are more likely to have a heightened sense of alertness regarding messages that contain emotional rather than purely factual content. Therefore, messages with emoticons may receive more scrutiny, and people are less likely to believe the message because they do not expect emotion in a factual rather than social exchange [7]. Therefore, our hypothesis becomes:

H5: People can better detect deception in 'social media like' text which includes emoticons over plain text.

This leads into our final hypothesis. The literature is clear that people are better at detecting truth than they are at detecting deception [6,18,31,32]. Accuracy rates for honesty are routinely as high as the 70 to 80% range, while accuracy rates for detecting deception are routinely in the 30% range [32]. Therefore, adding emotional content and richness may distract the receiver from the message intention and make honesty detection more difficult. If this is the case, we would expect to find that plain text makes the detection of truth easier. Therefore our 6th hypothesis is:

H6: Plain text is enough to detect honesty.

2. Methods

2.1. Subjects and sample

A sample of 600 subjects located in the United States was collected during the fall months of 2018. The panel was developed with the help of survey specialists from Qualtrics to ensure a representative respondent group. Respondents were stratified according to age (18–65+ years old), gender, and social media usage. The sample was 49.7% female and 50.3% male. No significant effects due to collected demographics were found. Fourteen respondents were removed due to poor quality of responses. Others had been pre-emptively filtered because they rated all snippets as indeterminate or failed attention checks. The analysis was conducted on a group of 535 respondents, each of whom responded to eight questions, for a total of 4280 responses. Each response ranged from 1 to 7, on a 7-point Likert scale. After removing the 860 responses of '4' or 'neutral,' 3420 responses remained. Of these, 1417 were plain text (588 of these were deceptive), 1418 were annotated text (568 of these were deceptive), and 1445 were text with emoticons (549 of these were deceptive). That means that 2863 responses included emotional content in addition to plain text.

2.2. Procedure

The study initially used a 2 (Text Veracity: honest or dishonest) x 3 design (Cues: Plain text vs Annotated Text vs Emoticons), with 6 levels. This was implemented using 8 independent judgements—4 with deceptive messages and 4 with truthful messages for text veracity. Each participant viewed all 8 text snippets assigned in random order. In addition, each snippet randomly used 1 of 3 media representations (plain text, annotated text, or text with embedded emoticons) to provide the cues dimension of the design. The original content of the snippets related to scholarship interviewee comments that truthfully or deceptively described their background. To create the annotated texts, plain text transcripts were transcribed and then annotated regarding physical movements, coughs, yawns, pauses, and other cues observed on interview videos. For the text with emoticons, a small group of social media users inserted emoticons into the text snippets. Multiple researchers checked the annotations and emoticons to ensure they represented visual cues from the videos. For example, a firm face expression was represented as ⟨firm face⟩ in annotated text and as a ☹ in text with emoticons. A smile was represented as ⟨smile⟩ in an annotated text snippet and as ☺ in the text with emoticons. Paralanguage utterances such as umm, oh, and hmm were also added to the annotated transcript in a consistent manner [30]. Each text snippet with emoticons had five inserted symbols to ensure consistency across the entire sample. This was consistent with parameters found by Park et al. [44], who studied text message content and found that most users included emoticons in their messages (only 5.7% did not) and that the frequency of emoticon use indicated multiple emoticons per message (one emoticon used (37.7%), two to

Table 1
Odds ratio estimates for treatment and veracity.

Effect	Point Estimate	95% Wald Confidence Limits	
Treatment Annotated Text vs Plain Text	0.281	0.242	0.327
Treatment Emoticons in Text vs Plain Text	0.364	0.314	0.422
Veracity Dishonest Snippet vs Honest Snippet	0.768	0.682	0.865

three emoticons used (28.3%), four to five emoticons used (3.8%) and over six emoticons used (24.5%)).

2.3. Variables

The source material used in the survey was titled and described to provide a context. Participants were asked to determine the snippets' veracities after reading/viewing. An embedded survey required a decision which was not time-constrained, and the snippet remained on the screen so it could be reread if desired. Individuals assessed truthfulness or deception on a 7-point Likert scale, ranging from 1 (e.g. very honest) to 7 (e.g. very dishonest). A response of '4′ was considered indecisive and removed from the dataset.

3. Results

We first approached the data using a 2-way ANOVA in SAS 9.4. However, a violation of normality suggested this approach could not reliably be used (test for normality - Kolmogorov-Smirnov D = 0.194, p<.010). Instead, we used proc logistic in SAS 9.4 with a cumulative logit model and Fisher's scoring. The main effects model used treatment and statement veracity as independent variables in a 2 (Text Veracity: honest or dishonest) x 3 design (Cues: Plain text vs Annotated Text vs Emoticons), with 6 levels. Respondent rating was used as the dependent variable. The overall model was statistically significant (Wald Chi-Square = 319.981, df = 3, p < .000). Annotated text was considered the most dishonest (mean = 4.51, s.d. = 0.089), followed by text with emoticons (mean = 4.19, s.d. = 0.091), with plain text perceived as the most honest (mean = 2.98, s.d. = 0.076). Pairwise comparisons demonstrated that each treatment was statistically significant from the other two (See Table 1 for Odds Ratios).

The main effects were tested further with a test for the equality of proportions considering all 6 levels. Proc Freq with the riskdiff option was used in SAS 9.4 to conduct this test. The results were significant for the overall model (Wald Chi-Square = 322.172, df=5, p<.000). Fig. 1 illustrates the data broken down into the 6 levels. Based on the analyses conducted, H1 was supported.

H2 predicted that deception would be difficult to detect in plain text messages since these were devoid of any cues. We tested Hypothesis 2 using the Cochran-Mantel-Haenszel test, which is designed to determine significant difference in repeated measure, binary data sets [11,35,38]. A script was run in SAS 9.4 using PROC FREQ with the CMH2 option set to produce Cochran-Mantel-Haenszel statistics. The sample size used for the test was 1149. To qualify for inclusion, an item had to represent one of the plain text examinations. The outcome was statistically significant (CMH = 232.76, p<.0001). Deception was only detected 28.4% of the time in the plain text sample. Therefore, H2 was supported.

We used repeated measures linear regression, in SPSS Version 25, to test Hypotheses 3 and 4. The GENLIN command was used, with a binomial distribution and logit as the link function. Repeated measures were used, as each participant answered eight different questions. The main effects model used treatment as the independent variable and the correctness of the veracity judgment (a discrete variable with two possible values) as the dependent variable. The Bonferroni process, with α < 0.05, was used for pairwise comparisons. The analysis examined only the reactions to the false snippets. There were 588 deceptive plain text snippets, 569 annotated text snippets, and 549 text snippets with emoticons. The overall model was statistically significant (Wald Chi-Square = 213.409, df = 2, p < .000).

H3 predicted that participants would be more accurate at detecting deception in annotated text than in plain text snippets. The hypothesis was supported. The accuracy rate for plain text was 27% (standard error = 0.020), while the accuracy rate for annotated text was 63% (s.e. = 0.023). The difference between plain text and annotated text was statistically significant. H4 predicted that participants would be more accurate at detecting deception in text with emoticons than in plain text snippets. The hypothesis was supported. The 27% accuracy rate for plain text was less than the accuracy rate for text with emoticons at 61% (s.e. = 0.024). The difference between plain text and text with emoticons was statistically significant.

H5 predicted that truthful messages with emoticons were more likely to be distrusted than truthful plain text messages [63]. We tested Hypothesis 5 the same way we tested H4, except we used only the honest snippets in the analysis. There were 561 honest plain text snippets and 599 honest text snippets with emoticons. The overall model was statistically significant (Wald Chi-Square = 118.260, df = 2, p < .000). The accuracy rate for honest plain text was 73% (s.e. = 0.021), which was statistically significantly different from the accuracy rate for text with emoticons (51%, s.e. = 0.024). The differences in accuracy imply that text snippets with emoticons were less trusted, supporting H5.

H6 suggested that since people are better at detecting honesty than dishonesty, all that is needed to detect honesty is plain text. We tested this hypothesis using the generalized estimating equations (GEE) approach, designed to determine significant differences in repeated measure, binary data sets [33,50]. A script was run in SAS 9.4 using PROC GENMOD with repeated measures. The sample size used for the test was 1715. To qualify for inclusion, an item had to represent a non-deceptive message using plain text, annotated text, or text with emoticons. The outcomes were statistically significant (z = −9.95, p<.0001). Indicating model significance. Truth was detected in plain text 73.4% of the time. In the annotated text, it was detected 42.5% of the time and in the text with emoticons, it was detected 51.1% of the time. A Tukey-Kramer test for differences further revealed that plain text was significantly better for detecting honesty than annotated text (z=−10.60, p<.0001) and better for detecting honesty than text with emoticons (z=−8.72, p<.0001). Therefore, H6 was supported.

For a post hoc analysis, we looked at each of the eight questions in detail. Questions 1, 3, 5 and 7 all involved dishonest snippets. Questions 2, 4, 6 and 8 used honest snippets. Given there was only one response per participant per question, we could use one-way ANOVA to analyze differences within the responses to a question. For all the dishonest snippets, except for Question 3, participants who read the version of the snippet with emoticons were better at detecting deception than were those who read plain text only (Table 2). For the honest snippets, except for Question 2, participants who read the text only snippet were better at detecting deception than were those who read the text with emoticons. This pattern suggests that plain text is all that is needed to successfully detect honesty. Augmented text seems to get in the way of making that determination. On the other hand, when the text is dishonest, plain text is not enough for accurate detection. The presence of emoticons – either because they are in themselves are indications of specific deceptions or they signal dishonestly more generally – helps detect deception in text.

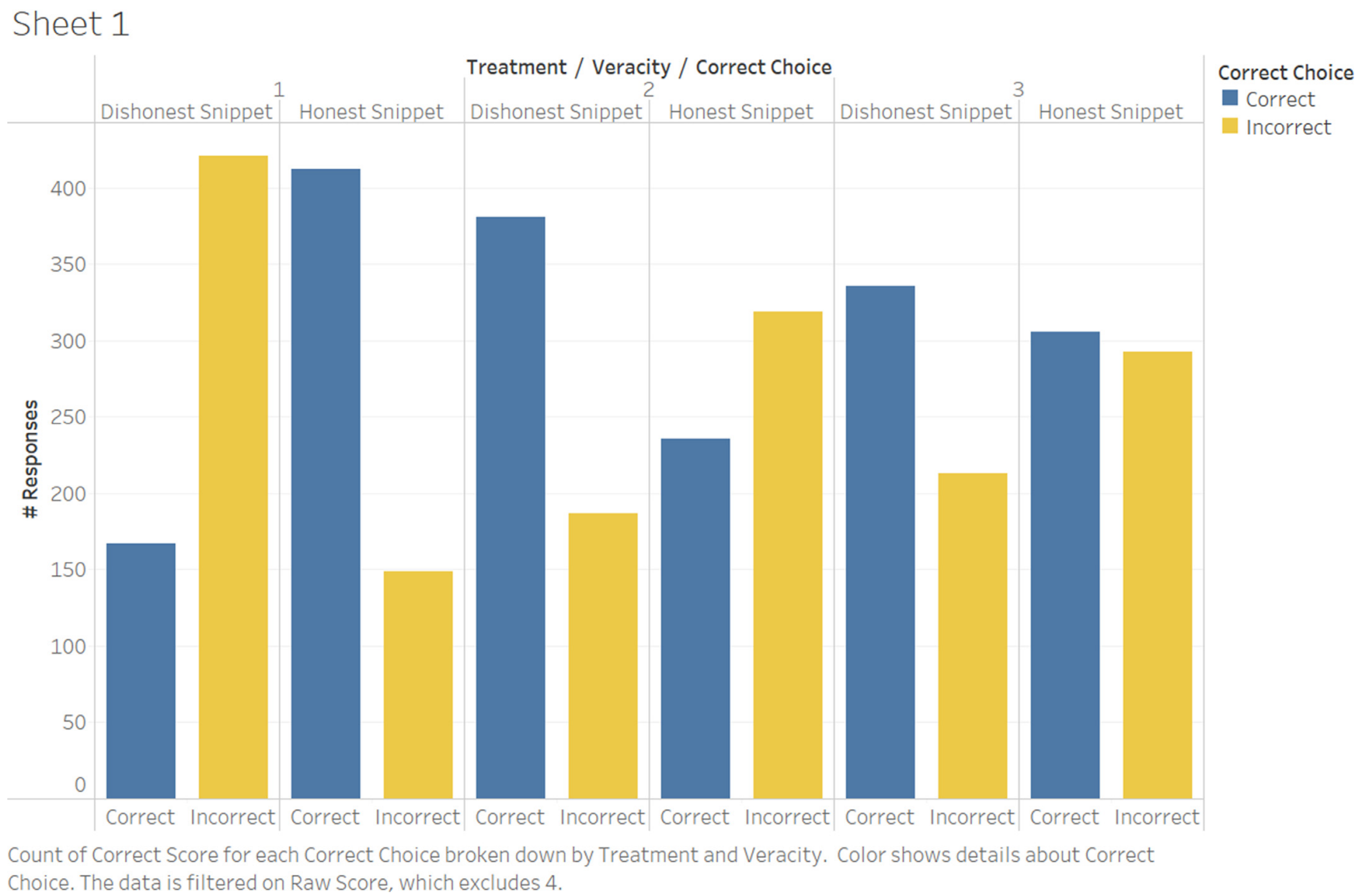

Fig. 1. Correct and incorrect responses by treatment (1=plain text, 2=annotated text, 3=emoticons).

Table 2
Plain text versus emoticons.

Question	Type	Plain text mean	Text with emoticons mean	Difference statistically significant at $p < .05$?
1	Dishonest	0.14 (0.347)	0.34 (0.474)	Yes
2	Honest	0.45 (0.499)	0.36 (0.480)	No
3	Dishonest	0.39 (0.488)	0.50 (0.502)	No
4	Honest	0.72 (0.450)	0.43 (0.482)	Yes
5	Dishonest	0.25 (0.433)	0.53 (0.501)	Yes
6	Honest	0.58 (0.495)	0.30 (0.458)	Yes
7	Dishonest	0.15 (0.358)	0.60 (0.492)	Yes
8	Honest	0.67 (0.473)	0.52 (0.501)	Yes

Standard deviations in parentheses.

4. Discussion

Several remedies have evolved to help enhance lean communication. Our study examined two of these: annotated text (paralanguage) and emoticons. We started with a broad examination of whether perceptions regarding the perceived truthfulness of messages with embedded emotional cues were different than those of subjects viewing the same messages without the cues. As expected, the findings regarding our first hypothesis showed that the cues significantly impacted perceptions, regardless of message interpretation [2]. Specifically, added cues tended to increase the perception that all communication was dishonest in a sample that was evenly split between honest and dishonest messages (e.g. mean score of 2.98 for messages with no emotional cues versus 4.35 for messages with emotional cues where 1 was honest and 7 was dishonest). Respondents' perceptions that the messages were dishonest increased by nearly 46% when cues were introduced.

We now knew embedding emotional or other non-verbal cues into messages changed recipients' perception. The next step in our exploration was to understand the nature of these perceptions. Prior research has established that non-verbal cues (e.g. leakage) in face-to-face communication provide indicators that deception may be present [19,20]. Therefore, it stands to reason that messages without cues would make deception more difficult to detect. Our second hypothesis considered only deceptive text messages which had no embedded cues. As expected, receivers were very poor at detecting deception in plain text. Our results indicated that when deceptive plain text was presented to the respondents, only 28.4% thought it was not truthful. This result was significantly different from chance.

Our third and fourth hypotheses examined two methods for embedding emotional or non-verbal cues into deceptive, plain text messages. The first used annotated text and the second used emoticons. We expected both methods to increase the ability of recipients to detect deception based on prior research into emotional leakage [20,21]. The results supported our hypotheses, with 67.1% of the receivers detecting deception in annotated text messages and 61.3% detecting deception in messages with embedded emoticons.

While these results are theoretically supported, it is possible that the same phenomenon could occur in truthful messages because people might inherently distrust enhanced text messages, which resembled postings found in social media. This seems to be a distinct possibility because we currently live in a world of fake news, alternate truths and widespread distrust in social media messages [1,3,16]. This perspective was further supported by data collected in the survey representing respondents who believed people were deceptive in social media messages (83% marked 'yes'). To investigate, we examined just truthful messages. In plain text, only 26.6% of the respondents incorrectly believed the messages to be deceptive. This value jumped to 48.9% in text with embedded emoticons. While both occur less than mere chance, we see that embedded emotional content did make the receivers more suspicious of message veracity.

We again looked at only honest messages with our final hypothesis. We posited that plain text would provide enough information to detect honesty, and this was supported: 73.4% of the respondents correctly believed the honest messages when these were presented in a plain text format.

Our results provide several interesting insights. First, deception was usually more accurately detected in annotated text or in text with embedded emoticons. Second, truths were more accurately detected in plain text, where the respondents did not observe leakage. This suggests additional questions: (1) did the emoticons tend to make people less likely to believe a statement? (2) was plain text better for truth? Answers to both questions appear consistent when viewed through the lens of leakage theory [20]. People expect emotional leakage to be present when messages are deceptive. This is particularly true when "leaked emotions [are] incongruous with the intended message" ([65], p. 66). Further, social media-like messages often are misunderstood [56], and emoticons can be used in ways that do not make sense to the receiver, although they may seem clear to the sender. In fact, many emoticons have obscure, unclear or multiple meanings, particularly when culture or other factors are considered [43]. So, in the current study, the use of emoticons may have confused the receiver and as a result, a cautious response emerged which caused them to suspect deception.

Another possibility was the level of inserted emotion. Each message had 5 emoticons inserted for consistency. While this number is not unusual or unexpected [44], it may have been enough to make people feel unsure about the message content. Park et al. [44] further suggested that while emotion may be expected in social conversation, it is not expected in task-oriented interaction (e.g. work-related communication). When emotion is encountered, it may be viewed as suspicious, resulting in a sense of cognitive dissonance that naturally manifests as distrust. When a receiver develops a sense of cognitive dissonance, they will seek to resolve the sensation, and this may mean changing their perception from belief to disbelief in the sender's message. This same phenomenon has been used to train auditors in fraud/deception detection. Hobson et al. [[26], p. 1139] suggests that, "[cognitive dissonance] should help experienced auditors better identify fraud companies by reducing their learned tendency to discount fraud cues.

4.1. Practical implications

This research has several managerial implications. First, understanding that text-only messages are readily viewed as honest, and that deception is more difficult to detect in plain text (as compared to enhanced text message) is a powerful bit of information. Where less-than-honest messages might be helpful, as in business negotiations, the use of plain text without enhancements seems to make those deceptions harder to discover. Not only do plain text messages provide few cues to detection, they are not suspect in the way that enhanced messages are, in the way that they mimic social media posts, which many view as suspicious.

4.2. Limitations

Several limitations in the design and measurement of this study are present. First, data were collected via survey and are, therefore, subject to criticism common to this methodology. Another limitation is generalizability. The deception material and experimental treatments were developed in midwestern university settings in the United States.

CRediT author statement

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Joey George: Conceptualization, Methodology, Data curation, Writing- Original draft preparation, Validation, Writing- Reviewing and Editing.

Declaration of Competing Interest

The Author(s) declare(s) that there is no conflict of interest.

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