Untangling a Web of Lies:
Exploring Automated Detection of Deception in Computer-Mediated Communication

Contact Details
(In order of authorship)

1. Stephan Ludwig
Senior Lecturer in Marketing
Westminster Business School
University of Westminster
35 Marylebone Road
NW1 5LS London,
UK
Tel.: +44 (0) 2035 06 67 64
E-Mail: s.ludwig@westminster.ac.uk

2. Tom van Laer
Senior Lecturer in Marketing
Cass Business School
City University London
106 Bunhill Row
EC1Y 8TZ London,
UK
Tel.: +44 20 7040 0324
E-Mail: tvanlaer@city.ac.uk

3. Ko de Ruyter
Professor of Marketing
Cass Business School
City University London
106 Bunhill Row
EC1Y 8TZ London,
UK
E-Mail: Ko.De-Ruyter.1@city.ac.uk

4. Mike Friedman
Associated Researcher
Louvain School of Management
Catholic University of Louvain
Chaussée de Binche, 151
B-7000 Mons
Belgium
Tel.: +32 65 32 33 71
E-Mail: mike.friedman@uclouvain-mons.be

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Biographical Statements

Stephan Ludwig is a Senior Lecturer at the Department of Marketing & Business Strategy Westminster Business School. He has a Ph.D. in Marketing and eight years of consulting experience in marketing research for financial services, FMCGs and communication services. His research interests focus on communication design, e-commerce and marketing strategy and is published in leading international journals including the *Journal of Marketing, MIS Quarterly, IJEC,* and other outlets.

Tom van Laer is Senior Lecturer in Marketing at Cass Business School. His research appears in premier and leading academic journals, including the *Journal of Consumer Research, International Journal of Research in Marketing, Journal of Business Ethics, Journal of Interactive Marketing*, and other outlets. Tom's publications reflect his interest in storytelling, social media, and consumer behaviour. Previously, he was Assistant Professor at ESCP Europe Business School and a visiting scholar at the Universities of Sydney and New South Wales in Australia. He holds a doctorate in marketing (PhD) from Maastricht University, the Netherlands. Though Tom has won awards for his academic research, teaching, and media exposure, he still counts winning his high school's story-reading competition in 1995 as his most impressive accomplishment.

Ko de Ruyter is Professor of Marketing at Cass Business School, the UK. His research interests focus on social media, customer loyalty and environmental stewardship. He has published six books and numerous scholarly articles in among others the *Journal of Marketing, Management Science, Journal of Consumer Research, Journal of Retailing, Journal of the Academy of Marketing Science, International Journal of Research in Marketing, Decision Sciences, Organization Science, Marketing Letters, Journal of Management Studies, Journal of Business Research, Journal of Economic Psychology, Journal of Service Research, Information and Management, European Journal of Marketing and Accounting, Organisation, Society and MIS Quarterly.*

Mike Friedman is an Associated Researcher at the Louvain School of Management, Catholic University of Louvain, Belgium. He holds a Ph.D. in social psychology from Texas A&M University. Mike's research interests include consumer motivations, brands and branding, and text analysis.

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Abstract

Safeguarding organizations against opportunism and severe deception in computer-mediated communication (CMC) presents a major challenge to CIOs and IT managers. New insights into linguistic cues of deception derive from the speech acts innate to CMC. Applying automated text analysis to archival email exchanges in a CMC system as part of a reward program, we assess the ability of word use (micro-level), message development (macro-level), and intertextual exchange cues (meta-level) to detect severe deception by business partners. We empirically assess the predictive ability of our framework using an ordinal multilevel regression model. Results indicate that deceivers minimize the use of referencing and self-deprecation but include more superfluous descriptions and flattery. Deceitful channel partners also over structure their arguments and rapidly mimic the linguistic style of the account manager across dyadic e-mail exchanges. Thanks to its diagnostic value, the proposed framework can support firms' decision-making and guide compliance monitoring system development.

Keywords and Phrases: CMC between business partners, deception severity, speech act theory, automated text analysis

Deceitful practices in business, ranging from white lies, flattery, and evasions to bald-faced falsification, appear to be endemic to all sorts of day-to-day business interactions [17, 65]. Recent research shows that deception is particularly common in business communications, with the more severe ones drastically interfering with the flow of information across organizations [1]. Deception in business can result in serious delicts, leading to lawsuits and in extreme cases, is costly to society at large. Estimations of the costs of deception in business-to-business (B2B) communication in the US range up to $200 billion annually [1]. Given information technology (IT)'s pervasiveness in facilitating most business communications it is little surprising that computer-mediated communication (CMC) is also frequently used to transmit deceitful information in business [2-4]. Intentionally designed "to foster a false belief or conclusion by the receiver" [5, p.205], deception is particularly a common problem in computer-mediated business requests and negotiations because a successful lie can earn one side tremendous advantages [1]. Furthermore, the isolation and relative anonymity of the communicators reduces interpersonal awareness and increases the truth bias. Moreover, unstructured CMC is mostly text based (e.g., e-mail), as opposed to the combination of spoken words, tone, and facial expressions used in face-to-face talks. Therefore, it is difficult to ascertain the other person's goals, mood, and motives [6]. Given the insufficient resources and the poor ability of humans to detect deception in communication in general [7] and in CMC in particular [8, 9], safeguarding organizations against opportunism and severe deception detection thus presents a major challenge to CIOs and IT managers [6].

Although much research into deception in general communication has been conducted in the past several years [7], little support is provided for the detection of deception severity in the CMC field. An emerging body of research considers the viability of simple text features (i.e., single word cues) as predictors of deception [10]. Yet, such information system research essentially enters linguistic terrain, which requires richer text interpretations to develop a more subtle profile of deception severity [2, 11]. Such interpretations appear innate to speech act theory [12, 13]. This theory proposes that any form of expression, whether vocal or textual, represents the performance of an act, intended at invoking some behavior in the receiver. Where a truthful act is directly related to the intent, the purpose of insincere acts is to keep the illegitimacy of the speaker's claim hidden [14]. In the absence of an unambiguous cue, higher level linguistic context may matter greatly when investigating deception [7]. Accordingly, beyond single (or combinations of) words used in current CMC analysis systems, message development and exchanges may serve as further cues to detect deception [6]. Using conceptualizations of speech acts [12, 13, 15] this paper proposes and empirically validates a design framework for text analysis of deception detection in CMC.

First, we clarify the notion of insincere speech act and its implication in terms of deception, which constitutes the relevance of our model. We illustrate the various ways linguistic indicators relate to deception severity along its established dimensions of falsification, concealment, and equivocation [16]. Previous experimental, information systems research pertaining to instant messaging and chat room conversations suggests mixed insights about linguistic cues of deception [9, 17], but a rigorous field test of a theory-driven, comprehensive framework is lacking [11]. We systematically review the IS and communication literature to develop such a multilevel framework, accounting for the subtleties and complexities of deceitful communication in CMC.

Second, we focus on within-message argument development. Previous information systems research has treated text as a unitary variable [18] or considered single (or combinations of) words [19]. However, in reality, severe deception often is developed sequentially across a series of sentences, where relative coherence or discord may also indicate deception [20]. To uncover how business partners purposefully develop deception across a sequence of sentences, we therefore consider messages' macro structures in CMC. Thus, we extend speech act theory to include the macro-level structural features evincing deceitful CMC.

Third, we focus on the between-message interactional exchanges and assess the implications of linguistic style matching (LSM) for deception. Deceivers have an interest to make themselves appear more accommodating and likeable [21], which may manifest itself in close and rapid alignment of their communication style with that of their conversant across interactional exchanges. Following recent information systems research, such style alignment in CMC is symbolically reflected and may be measured considering the linguistic style matching (LSM) between conversant [22]. Extending speech act theory to the meta-level of conversation, we explore whether rapid LSM indicates deception in CMC.

In the next section, we review the insights from research on deception in the CMC field in particular, highlighting the relevance of a multilevel framework and providing conceptual clarification of the terminology adopted in deception research. We formulate hypotheses aimed at assessing the relative predictions of deception severity in CMC between businesses and test these hypotheses with a large set of requests discussed as part of a reward program run by a global *Fortune* 100 company. We conclude by outlining the theoretical and practical implications of our findings with regard to the design and management of enhanced information systems to detect deception severity.

Speech Act Theory on Deception

Austin [12] coins the notion of speech acts. Using acting as a metaphor for speaking, he conceptualizes speech, whether vocal or textual, as the performance of "acts" that are aimed at invoking certain behavior, such as commanding, confirming, or questioning. He distinguishes analytically between locutionary speech acts, the acts of saying something;

illocutionary speech acts, what individuals intend to achieve in saying something; and lastly perlocutionary speech acts, the actual effects of utterances on their audience. Searle [23] anticipates the linguistic discipline's focus on illocutionary acts by arguing that linguistic cues at a higher level than "mere" words convey the intention of a speaker to tell the truth (or not) and, as a result, make a speech into an (in)sincere act. He also introduces the notion of insincere speech acts in which the connection between the truth and the utterance is not clear but troubled. Habermas [24, 25] later describes the speaker's intention to tell the truth (or not) as a condition that validates a speech act. Notably, this intention of the speaker makes the legitimacy or the truth of a communication (in)accessible to a receiver, thus marking a clear separation in terms of speaker/receiver and insincere/sincere, or deceitful/truthful.

Since speech act's conceptualization, research has demonstrated that a speaker can install false beliefs in a receiver [23]. Subsequent studies have confirmed that an insincere speech act can succeed in persuading its receiver that the claim is legitimate and true [7]. If undetected, the effects can be strong and long-lasting. The effect that insincere speech acts achieve is deception of the claim receiver. However, the performance of insincere speech acts is markedly different from that of sincere speech acts, making it possible to detect liars. CMC is especially vulnerable to deception, as unstructured data is exchanged through emails [6, 26]. The cue availability heuristics [27], information asymmetries, informational richness, and processing complexities [2] associated with these exchanges provide fertile ground for deception. Three established dimensions of deception severity—falsification, concealment, and equivocation [28]drive these insincere speech acts.

First, insincere speech acts may require that liars communicate claims that they consider false—the deceitful illocution. Second and third, liars may deceive through two main components: concealment and equivocation. In avoiding detection, liars may provide incomplete information or they may opt to be intentionally evasive, indirect, or vague.

Together, falsification, concealment, and equivocation offer an explanation for an insincere speech act to appear legitimate and true. In accordance with these features, we define (in) sincerity of a speech act as the extent to which a liar aims to persuade a receiver by (1) falsification to make a claim appear legitimate and a liar avoids detection by (2) concealment and (3) equivocation, which leads him or her to leak insincerity in linguistic features during communicative acts.

Towards a Multilevel Framework of Deception in CMC

Insincere speech acts are an unethical form of communication and as such have attracted much scholarly attention [7]. Several theories, such as the leakage [29] and four factor theory [30], explain deception at the single-word level. Leakage refers to involuntary physiological processes that "leak" unbidden in the form of tell-tale cues to deception; the physiological processes are the four factors of arousal, negative affect, cognitive load, and attempted control. Table 1 contains an overview of studies focused on uses of (combinations of) words as indicators of deception. Although various peculiar uses of specific ranges or combinations of words appear distinctly manifest or absent, the empirical evidence from these studies is mixed and inconclusive, which hampers the diagnosticity and predictive ability of linguistic cues of deception.

[Please insert Table 1 about here]

Matsumoto and Hwang [10] highlight that these mixed findings primarily stem from an exclusive focus on monologues or comparative writing, rather than conversations as they occur in real, interactive exchanges. Extending prior classifications of deception, Xiao and Benbasat [31] also query the lack of insight into deception in inter-organizational CMC and DePaulo et al. [7] observe that deception studies have been conducted almost exclusively in university laboratories. As Miller and Stiff [32] caution, experiment participants have little motivation to get away with their lie, minimal actual interaction with other participants, and an artificially high degree of self-consciousness.

The equivocality of existing findings might further stem from the inability of such micro-level cues to do justice to nuanced, carefully crafted, deceitful communication [10]. Following this line of reasoning, Carlson et al. [11] indicate that no single behavior or specific cue sufficiently determines deception; nor the severity thereof. Accordingly, the feeling/thinking cues theory [29, 33] conceptualizes “leaks” at the macro level (e.g., an inconsistent or over-rehearsed claim). Buller and Burgoon [21] further conceptualize deception as interpersonal: Liars rely on adapting the style of their claim’s presentation to (their perception of) the receivers’ preferences. Similarly, self-presentational theory [7] demonstrates that liars are more concerned with their impression on others, which is less present in truth speakers. This multilevel approach to deception fully aligns with Abbasi and Chen [2] calling for externally valid, text mining research that considers the information embedded in the structure and exchange of textual CMC.

In sum, even though speech act theory has laid the groundwork for understanding deception as actions situated at multiple levels, empirical evidence for this has essentially remained at the micro level of (combinations of) words [34]. Thus, a comprehensive model is overdue not only to advance knowledge on deception (severity) detection per se but also to complement speech act theory. Accordingly, we extend deception research to the macro-level of deceitful claims as bodies of texts patterned by structural features and explicitly consider conversation as a crucial resource for interpreting deception as an interactive and socially located phenomenon. Hence, we use a comprehensive approach, spanning all three levels of communication, to develop a multilevel framework for deception severity in CMC that forms the basis for our hypotheses. Consider for instance two different request formulations by business partners in our study’s data set:

Business partner A: *Good day! We have received an enquiry for the [...] reward we requested. Could you please kindly help to check whether the […] has successfully registered the […]? If not then there seems to be an error in your system with processing the reward points […].Thanks very much for your help!*

Business partner B: *Is this a joke? I sent in an email asking about an offering of yours on Sept 5. I got an email acknowledging my request, but I received nothing else for over a month. About a week later, […] went ahead and ordered some items with our reward points, including the item I asked about […]. Once again, I got an acknowledgement that you received my email, but absolutely nothing else […]. Thanks*

Notice that both partners essentially request the same thing, a redemption of rewards as part of the partner program. Yet, already at the micro level, their word use differs. For example, partner A, whom the account manager identified to have made a severely deceitful request here, makes much less effort to expound the situation. He also uses fewer reference words (e.g., personal pronouns like I, them, and her), avoids contextually embedding the situation (e.g., providing times and places), and avoids providing other clarifying descriptions (e.g., adjectives). Partner B, whom the account managers identified to be rightfully frustrated and her request fully legitimate, uses more reference words (e.g., I, my) and makes an effort to contextualize her request (e.g., on Sept 5, over a month).

Although the macro-level cues are not easy to detect, consider the partner A's request full of causality and cognitive process words in every sentence (e.g., although, if, whether). Partner B instead tends to use these words more sporadically, leaving her argument development partially unstructured. At the meta level (interactional-level), Buller and Burgoon [21] propose that deceivers, in an attempt to invoke liking and empathy, mimic (their perceptions of) receivers' behavior. Thus, we would expect partner A to rapidly adapt to the writing behavior or linguistic style of his conversation partner during the e-mail exchange process [35].

Micro-Level Deception Cues

First, corroborating mixed findings at the micro level, we discern five word and word-combination cues of deception severity and develop hypotheses about their predictive value.

Referencing. Severe deceivers tend to withdraw and communicate less. Ekman [33] as well as Zuckerman, DePaulo and Rosenthal [30] show that deceivers experience feelings of guilt or apprehension about deceiving, so they are less forthcoming and appear distant. Such acts appear as a lack of "categorical references" [23, p.74]. The speech act of referencing pinpoints and identifies the people involved [7], whereas fewer references to the self or others (e.g., I, them, her) constitute linguistic constructions that distance the speaker from his or her message [36]. For example, "One could believe this" is more impersonal than "I could believe this." As such we hypothesize that, in B2B communication, fewer personal pronouns reflect partners' intentions to distance themselves from their message as well as a linguistic cue of more severe deception:

H_{1a}: Referencing relates negatively to deception severity in CMC.

Contextual embedding. Deceivers avoid describing the context [37]. Contextual embedding connects a message to actual events [12]. Linguistically, the extent to which speakers substantiate the circumstances of an account is manifest in their use of spatial and temporal context words (e.g., down, in, end, until) [38]. Deceivers either choose not to [21] or are unable to [37] describe situational circumstances in their account. In CMC, the reluctance or inability to embed messages, marked by the use of fewer context words, may indicate the severity of a business partner's deception. Thus:

H_{1b}: Contextual embedding relates negatively to deception severity in CMC.

Detailing. Severe deceivers use relatively fewer descriptions in their accounts [7]. From a speech act perspective, descriptive adjectives explicate an account [23]. Although Zaparniuk, Yuille, and Taylor [38] find that deceivers strategically bury the deception in "vivid and concrete descriptions of superfluous details" that make a message seem rich in—albeit unnecessary—specifics, most research suggests that deceivers tend to avoid detailed descriptions [e.g., 7]. We hypothesize that in CMC less descriptive adjectives indicate more severe deception, as the partners aim to avoid being caught on details.

H_{1c}: Detailing relates negatively to deception severity in CMC.

Self-deprecating. Knowing their intent is insincere, deceivers work to rule out uncertainty about their own actions [39]. For example, deceivers consciously exclude "unfavorable, self-incriminating details" [38, p. 344]. Linguistically, self-deprecation becomes evident through references to the self (first-person pronouns) in combination with discrepancy words (e.g., "I could," "I should," "it might be just me"; [40]). We propose that in CMC severely deceitful partners are apprehensive of questions about the legitimacy or appropriateness of their own conduct and thus less likely to disparage it. Therefore, we hypothesize:

H_{1d}: Self-deprecating relates negatively to deception severity in CMC.

Flattering. Deceivers are motivated to appear increasingly pleasant and thus use compliments and flattery [21]. Flattery seeks to increase or consolidate rapport with the conversant [41, p.442] and is common in CMC [42, 43]. Linguistically, flattery results from the use of achievement words (e.g., "the best," "hero," "great") in combination with a reference to the conversant (second-person pronouns) [41]. Though flattery in itself is acceptable in CMC, more flattery may reflect an ulterior, more harmful motive through faked solidarity by business partners [21, 41]. Therefore, we hypothesize:

H_{1e}: Flattering relates positively to deception severity in CMC.

Macro-Level Deception Cues

Macro-level speech acts reflect how a speaker develops and structures her rationale (e.g., coherence, flow) [15]. Ekman [33] and DePaulo et al. [44] emphasize the need to attend to such macro aspects in communication when assessing deception. For example, Ekman [33] notes that deceivers' fears of being caught, while aiming to be as convincing as possible, likely are manifest in the form of over-rehearsed arguments. Particularly if there is time to prepare (e.g., in e-mail exchanges), "too smooth a line may be the sign of a well-rehearsed con man" [45, p.185].

Linguistically, a cohesive level of argumentation across the series of sentences in a message, rather than varying between more and less reasoning, signals such consistent structuring (e.g., using words such as "because," "although," and "if" consistently in every sentence of a message). Even if messages contain arguments in several sentences, people naturally vary the reasoning intensity across those sentences [46]. Goldkuhl [20] identifies that deceivers' tendency to over-structure their message development gets exacerbated in highly motivating contexts, such as B2B communication. Accounting for within-message argument structuring in CMC should improve assessments of deception in B2B communication. Specifically, we posit that partners' cohesive argument structuring signals deception severity at the macro level.

H_2: Cohesive argument structuring relates positively to deception severity in CMC.

Meta-Level Deception Cues

Mimicking increases deceivers' likelihood of success, as Campbell et al. [47] explain: Recipients of messages from speakers who have assimilated their communication style, exhibit high levels of trust and tend to comply with requests. Such common ground perceptions in written communication may occur through the largely unconscious process of linguistic style matching (LSM) [35]. The convergent use of similar linguistic styles enhances understanding and perceptions of a common social identity while decreasing perceptions of social distance [22]. In online text-based negotiations, closer matches in function word usage (e.g., uses of pronouns, articles, conjunctions, prepositions, auxiliary verbs, high-frequency adverbs, negations, and quantifiers) as part of the interactional exchange increase interpersonal rapport and agreement among potential partners [48]. Although in B2B communication, partners may naturally accommodate each other's communication style due to genuine liking, their tendency to do so immediately and rapidly ought to be weaker. If during the interactional exchanges, partners rapidly alter their linguistic style to create a closer match with their conversant's linguistic style, this may indicate deception. In effect, we hypothesize:

> **H_3**: Rapid LSM during interactional exchanges relates positively to deception severity in CMC.

Empirical Study

Setting: The CMC Field

To test our hypotheses, we conducted a field study, in cooperation with a global *Fortune* 100 technology vendor. The data for our study comprises of archival, unstructured CMC (e-mails) between the company's account managers and its channel partners. All partners participate in the company's reward program, which includes approximately 120,000 partners worldwide. This research setting is relevant for testing our hypotheses for several reasons. First, emails serve as the sole means that partners use to request their rewards and on which the vendor’s account managers rely to assess the legitimacy of those requests. The absence of vocal (e.g., tone of voice) and physical cues (e.g., gaze, posture) makes a focus on linguistic markers imperative in such a CMC system. Second, in this reward program, significant monetary and non-monetary rewards (ranging from US$100 to US$100,000) are requested and issued. Third, the communication procedures and duration for each request within- and between-partners are very similar, increasing the comparability of the requests.

Sample

The sample consisted of 16,768 e-mails about reward requests, requested and processed between 1 June 2013 and 4 February 2014. The reward program is set up to award monetary incentives for partners’ sales and training performance. All CMC with partners therefore included monetary reward pay-outs due to their actual (or fabricated) performances. The program incorporates 11 different languages, but for feasibility and to ensure robust insights, we only included messages written in English in our sample. In addition, for the text analysis part of our measurement development we used the Linguistic Inquiry and Word Count (LIWC) text mining software which is primarily validated in the English language context [49]. We manually corrected all spelling mistakes and removed automated e-mails (e.g., out-of-office replies), resulting in a final sample of 8,886 e-mails (4,496 from partners and 4,390 from account managers), concerning 2,420 requests made by 1,320 partners. On average, each partner wrote 3 e-mails per request, which contained an average of 5 sentences and 20 words per sentence.

Measurement Development

Although the request was generally presented in the first e-mail a partner sent, the discussion about its legitimacy could take place over several, sequential interactive exchanges and thus span several e-mails. We first derived our cues, using the LIWC software, at the e-mail level, using words, word combinations, and the overall structure of the email. Meta-level cues (i.e., LSM) were measured at the interactional exchange level of emails. We then aggregated all scores to the request level. Our dependent measure—deception severity—the vendor's account managers determined externally for each request, investigating first whether a request was legitimate and then how severe the deception was, using the dimensions which Buller et al. [16] established. We outline our measure development below.

Dependent variable. In accordance with recent conceptualizations of deception in information systems research [31] and drawing on Buller and Burgoon [21], we asked the account managers to investigate and evaluate all reward requests in the sample. Prior to the observation period, during which five managers investigated all reward requests, they were briefed that the study was intended to uncover linguistic elements which would relate to deceitful reward requests. Similar to Burgoon et al.'s [50] approach, we instructed the managers to attribute a score of 1 if (following their investigation) a request was completely legitimate and truthful. If this was not the case we asked them to rate the overall deception severity (scored 2-5) based on the extent to which statements were untrue (falsification), seemed to omit or withhold relevant information (concealment), and/or requests seemed evasive, indirect, or vague (equivocation).Thereby all requests were judged on a single-item, 5-point Likert-type scale where the most severely deceitful requests scored 5.

Independent variables. We considered three levels of speech acts: micro- (i.e., word use and combination of word uses), macro- (i.e., within-message development), and meta-level (i.e., between-message interactional exchanges). We provide illustrative examples in Table 2. To ensure an overall deductive approach which future scholars and IS practitioners find generalizable and easily replicable, we followed Tausczik and Pennebaker's [49] approach and text mined all partner emails, using LIWC dictionaries and the LIWC program, rather than building dictionaries based on specific text samples in our dataset.

Accordingly, we determined *referencing* to self and others as the ratio of personal pronouns to the total amount of words in an e-mail. We operationalized *contextual embedding* as the proportion of relativity words. For *detailing*, we measured the proportion of adjectives. Because no LIWC text mining dictionary exists for adjectives, we compiled a dictionary with 1,656 unique adjectives for this study, using online dictionary sources (i.e., enchantedlearning.com, the Oxford dictionary, thesaurus.com, and yourdictionary.com). For each of the text-mined, micro-level, speech act cues (Speech act cue_c), we constructed a request-level measure by dividing the number of cue words (CueWords) in a particular speech act category (j) within the e-mail (e) by the total amount of words (Words) in that e-mail (e). We then calculated the average ratio across all e-mails (E) for the same request (r). Our formula for calculating these speech act cues is thus:

$$\text{Speech act cue}_{\text{rj}} = \frac{\sum_{e \in r} \frac{\text{CueWords}_{\text{ej}}}{\text{Words}_{\text{e}}}}{\text{E}}, \tag{1}$$

where $speech\ act\ cue_{rj}$ represents either referencing, contextual embedding, or detailing, respectively.

To construct the combinations of word use measures of self-deprecating and flattering, we next text mined the proportion of co-occurrences within each individual sentence of first-person pronouns and discrepancy words, and then second-person pronouns and achievement words. Conservatively, we measured only co-occurrences for which a pronoun was the only one in that sentence. Thus, we were certain that either the partner or the account manager was the sole subject of the sentence. We created these composite speech act cues ($\text{Composite speech act cue}_c$) by summing the amount of co-occurrences in an e-mail (e) first, then aggregating these use intensities across all e-mails (E) for a particular request (r). Our formula for calculating these composite speech act cues is thus

$$\text{Composite speech act cue}_{\text{rj}} = \frac{\sum_{e \in r} \left(\text{Cooccurence of CueWords}_{\text{ej}} \right)}{E}, \quad (2)$$

where *composite speech act cue$_{rj}$* represents either self-deprecating or flattering.

Next, to construct the measure of structuring across the sentences of an e-mail, we computed variation in the cognitive process words. Most research that has examined writing behavior (dis)similarities uses direct consensus models (i.e., taking the average as the preferred level of aggregation). Yet recent research highlights that within-message variability or dispersion composition models might assess writing behavior and its implications more appropriately [51]. We therefore created an argument structuring measure in which we (1) summed the use of cognitive process words in each sentence in each e-mail, (2) calculated the structuring at the e-mail level as 1 divided by the within-e-mail variability in cognitive process word uses across all sentences, and (3) aggregated e-mail level coherences across all e-mails in a particular request (r).

For LSM, we followed recent research on interactional exchanges in CMC [22] and calculated it as the degree to which a partner produces usage intensities of function words that are similar to those the account manager used in the previous e-mail. First, we text mined the proportion of function word (CueWords) uses for each of the nine function word categories [35]. These categories comprise all 464 function words in the English language: articles, auxiliary verbs, common adverbs, conjunctions, impersonal pronouns, personal pronouns, prepositions, negations, and quantifiers. We measured the proportion of function words (Wordcue) for each e-mail (e) and for each function word category (j) by dividing the number of words belonging to the particular function word category by the number of words in the same e-mail (e):

$$\text{Speech act cue}_{\text{ej}} = \left(\frac{\text{CueWords}_{\text{ej}}}{\text{Words}_{\text{e}}} \right) \quad (3)$$

Second, we derived the degree of a partner's LSM in each individual request (c) for each function word category (j) separately. The differential use of each function word category (j), between the account manager's (m) previous e-mail (T1) and the partner's (p) response e-mail (T2), came from the formula:

$$\mathrm{LSM}_{\mathrm{rj}} = 1 - \frac{\left(|\mathrm{CueWords}_{\mathrm{mej}}^{\mathrm{T1}} - \mathrm{CueWords}_{\mathrm{pej}}^{\mathrm{T2}}|\right)}{\left(|\mathrm{CueWords}_{\mathrm{mej}}^{\mathrm{T1}} + \mathrm{CueWords}_{\mathrm{pej}}^{\mathrm{T2}} + 0.0001|\right)}, \tag{4}$$

where $\mathrm{LSM}_{\mathrm{cj}}$ is the degree of overlap between the usage intensity of a function word category (j) by the partner (p) and the usage intensity of the same function word category (j) by the account manager (m). We added .0001 to the denominator to prevent empty sets. We calculated the partner's overall LSM at the e-mail level by averaging the nine separate degrees of LSM for each function word category. Finally, we calculated median partner LSM across all e-mails for a particular request.

[Please insert Table 2 about here]

Control variables. In addition to the speech act cues at the request level, we controlled for demographics, which may affect people's writing styles, at the partner level. Specifically, following previous research [e.g., 52, 53], we controlled for years of work experience in the field ($\mathrm{experience}_{\mathrm{p}}$) of 1073 partners, and their gender ($\mathrm{sex}_{\mathrm{p}}$), coded as 1 = female and 0 = male, for 1223 partners. We also coded whether they included an e-mail signature ($\mathrm{signature}_{\mathrm{r}}$) (coded 1) or not (coded 0). Research suggests the relative motivation to deceive may alleviate the leakage effects. To rule out such an effect as an alternative explanation for our deception severity measure, we included scaled variables for the factored monetary amount for 940 request cases and account size of 168 partners. We assigned all missing observations (where we did not have the background information on experience, gender, monetary amount of the request and account size) a score of zero, for each variable after standardization (i.e., assigned missing observations the mean value), then included the dummies in our multilevel regression analyses to control for missing observations (for a discussion of this standard imputation technique, see [45]). Therefore, we were able to use the full set of e-mails and requests collected to analyze speech act cues that were not missing due to a lower level of abstraction, such as simple word use or were lacking partner-level observations. Furthermore, deception severity may also relate to the writers' ability to converse in the English language. While English is the common global business language, we included a dummy variable coded 1 if a partner request was send from a native English-speaking country (e.g., Australia, India, the UK, the US, etc.) or 0 if not (e.g., Belgium, Germany, the Netherlands, etc.) to account for English language ability. Importantly, incidences where partners stopped responding to questions were likely to be cases where they gave up trying to deceive in a CMC sequence and hence may further predict deception severity. Accordingly, we text mined the account managers' replies for question marks ("?"), indicating a request for more information in a communicative sequence. We dummy coded all request communication streams and denoted a 1 if the very last email in the email exchange included a request (question) by the manager and there was no later response by the partner. All other requests were coded 0. Finally to control for potentially systematic disagreement between individual managers from one-another, we include 4 dummy variables (D_{M1}-D_{M4}) in all our models which control for the 5 managers who rated a particular request scenario.

[Please insert Table 3 about here]

Results

To capture the estimates of the explanatory variables at the request and partner levels and thereby predict deception severity in individual requests, we specified a series of multilevel regression models, often referred to as hierarchical linear models (HLMs). This approach is appropriate for the current data structure, because it accounts for interdependencies among requests (e.g., multiple requests by the same partner), whereas standard regression techniques do not and instead assume that each observation is independent of the others [54]. Our data contained multiple requests nested within any given partner, and the HLM modeling approach appropriately controlled for the possibility that communication behavior in e-mails from the same partner would be more similar to one another than to e-mails from another partner. It also supported the simultaneous testing of the explanatory variables at the request and partner levels [55].

Before estimating the hypothesized relationships, we sought to determine whether there was any significant between-group variation in our dependent variable, a prerequisite for conducting multilevel analysis [56]. We first estimated a baseline ordinal regression model (intercept only) that included only the dependent variable (deception severity), then conducted a baseline multilevel ordinal regression (intercept only) that included deception severity as the dependent variable and a random effect for the partner as a grouping variable. A likelihood ratio test indicated that the multilevel ordinal regression model provided significantly better fit than the non-nested ordinal regression model ($\chi^2_{(1)} = 643.93$, $p < .001$), indicating the appropriateness of multilevel modeling for testing our hypotheses.

To determine the extent to which the variation in deception severity was due to the grouping variable (partners), we calculated the intra-class correlation (ICC) statistic for multilevel ordinal regression models [56], which reveals a ratio of between-group variance to total variance. The ICC value of .72 indicated that differences between partners, in terms of the severity of their deception, accounted for a large percentage of the total variance in deception severity. Certain partners were consistently less (or more) severe. We thus found convincing evidence that partner characteristics can exert direct influences on the severity of their deception.

We next specified a series of multilevel ordinal regression models to estimate the effect of the antecedent request- and partner-level variables on deception severity. We specified this model because of the skewed distribution of our deception severity measure, with 59.5% of requests identified as truthful (i.e., coded 1), 33.8% deceitful requests (coded 2 or 3), and 6.7% severely deceitful requests (coded as 4 or 5), We relied on the R "ordinal" package [57] to estimate the models, beginning with the intercept only Model 0. We introduced the individual-level variables related to micro-level speech act cues in Model 1, then included individual-level variables related to macro-level speech act cues in Model 2. We accounted for the individual-level variables related to the meta-level speech act cues in Model 3. The group-level covariates remained for all consecutive models (1–3) to ensure comparability (see table 4). We assume an independent correlation matrix. The correlation matrix in Table 3 and the maximum variance inflation factor score (1.77) indicated no potential threat of multicollinearity. For interpretability, we standardized all predictor variables at the request level before conducting the analyses, turning each variable into a z-value. Using χ^2 difference tests, we confirmed that the request- and channel partner-level explanatory variables added explanatory power to the final model (see Table 4, Models 0–3). Model 1 provided a better fit ($\chi^2_{(10)} = 219.14$, $p < .001$) than Model 0. Model 2 yielded a significantly better fit than Model 1 ($\chi^2_{(2)} = 8.73$, $p < .01$), and Model 3 had substantially more explanatory power than Model 2 ($\chi^2_{(2)} = 11.73$, $p < .001$). We took all the standardized estimates from our final Model 3; the estimates provided support for most of the hypotheses.

[Please insert Table 4 about here]

For each explanatory variable in our models, we calculated the odds ratio (OR) as a measure of the effect size, such that it provides the odds of a one-unit increase in deception severity, given a one-unit increase in the explanatory variable, *ceteris paribus*. An OR greater than 1 indicates an increase in the odds of deception severity with increases in the explanatory variable, whereas an OR less than 1 indicates a decrease in those odds when the explanatory variable increases. Because we standardized the continuous explanatory variables in our models prior to analysis, the OR indicates the odds of increasing one unit in deception severity, given a one standard deviation increase in the variables. For example, in the final model, the OR for $structuring_r$ was 1.5, so when $structuring_r$ increased by one standard deviation in a request, the odds of deception severity increasing by one unit should be multiplied by 1.5. This intuitive ratio provides a means to explain the effect size of each individual explanatory variable, as well as compare the effect sizes across different explanatory variables.

We report the effects of the micro-, macro-, and meta-level speech act cues in Table 4. First, we considered each micro-level cue separately. The results support our overall prediction that deception severity co-varies with different (combinations of) word uses; this co-variation was statistically significant and negative for referencing (β_1 = -.31, p < .01), positive for detailing (β_3 = .13, p < .05), negative for self-depreciating (β_4 = -.17, p < .05), and positive for flattering (β_5 = .17, p < .01), in support of H_{1a}, H_{1c}, H_{1d}, and H_{1e}. However, no statistically significant effect emerged for contextual embedding (β_2 = -.09, p = .18), so we cannot confirm H_{1b}. Second, we examined the effect of macro-level speech act cues and found that, consistent with H_2, cohesive structuring related significantly and positively to deception severity (β_6 = .35, p < .01). Third, regarding the effect of meta-level speech act cues, LSM was statistically significant (β_7 = .26, p < .01), in support of H_3, such that rapid LSM during interactional exchanges indicated more severe deception. For robustness purposes and to derive the linguistic effects in isolation, we re-analyzed model 3 excluding all control variables. These results remain similar, with no difference in significance for any of the effects reported above. Fourth, the findings pertaining to the control variables indicated that deception severity did not differ with channel partners' use of an e-mail signature. We also did not find a significant relationship between the monetary amount of the request (β_{10} = -.28, p = .12) and the account size of the partner (β_{14} = -.30, p = .26) on the one hand and deception severity on the other. In line with Anders et al. [53] we found that working experience and deception severity relate negatively, such that channel partners with more working experience appeared less deceitful (β_{11} = -.55, p < .05). Furthermore, in line with Hitsch et al. [52], women were significantly less deceitful than men (β_{12} = -.76, p < .05). Requests originating from English-speaking countries were positively and significantly related to deception severity (β_{13} = .90, p < .01). The failure to respond to a request by the managers further significantly related to partners' deception severity (β_9 = .26, p < .01). None of the dummy variables for the account managers were significantly related to deception severity, ruling out potential bias due to systematic differences in deception severity ratings. Using a classification table, we found that our model accurately classifies 70.13% of requests into legitimate and truthful (score 1) or illegitimate and deceitful (score 2-5). Excluding the partner-level control variables and including only the linguistic cues achieved an accuracy of 60.02%.

Notably, for all models we used all communication incidences (e.g., several emails per request). More interactions may however have meant a greater opportunity for the company to scrutinize the partner. Thus, in the later email exchanges, the deceiver may have had less degrees of freedom to, for example, withhold details. This may have lead to the nonsignificant relationship between an increased use of adjectives and deception severity. Therefore, as a further post-hoc examination, we re-conducted our final model including only the first, incoming emails per request (excluding LSM since this is an exchange-based, meta-level cue). We find that, when considering first emails only, the effects remain the similar, with the exception of flattery (β_{5new} = .04, p = .53) and cohesive structuring (β_{6new} = .17, p = .08). Offering an explanation for some of the discrepancies between previous experimental research that focused on deceptive monologues and research that focused on communicative cues in dialogues, this result shows that flattering and structuring, in addition to being micro- and macro-level cues, may well be partly meta-level communicative acts too.

Discussion and Conclusion

With CMC as a primary means to support coordination and decision-making in business-to-business (B2B) relationships, it is important to explore how to counter the vulnerabilities to deception that may result from its use. While extensive literature addresses the benefits of information-sharing between businesses, such as the potential generation of additional relational rents [58], limited research is devoted to uncovering means to safeguard against falsification, concealment, and equivocation in these systems [31]. Some deception is tolerated in business interaction, yet severe deception negatively affects performance and increases management costs [59]. The complexities and subtleties of deception, along with a barrage of CMC employees face every day, however, makes detecting deception a formidable challenge for CIOs and IT managers [6]. In this paper, we develop a framework for deception detection that may aid the design and management of enhanced information systems. While there is voluminous research on deception and on CMC, there is a relative scarcity of theoretical and empirical work at their intersection, especially for B2B communication. In line with recent conceptualizations of information systems as symbolic action systems [60], our study is firmly grounded in speech act theory and advocates a multilevel framework, incorporating single words (i.e., micro-level), structural (i.e., macro-level) and interactional (i.e., meta-level) speech acts. This study contributes to the extant information systems research on CMC-based deception in three ways.

Corroborating experimental research in CMC, we found that four micro-level speech acts relate to deception severity in such B2B communication. Severely deceitful CMC lacked self- and other-referencing (e.g., fewer personal pronouns), likely because partners sought to draw less attention to and avoid mentions of the people involved in the message [10, 36]. Business partners seemed to dismiss ownership of and put psychological distance between themselves and the deceitful message. Contrary to the relationship we predicted, detailing (e.g., the use of adjectives such as "sublime," "brilliant") appeared positively related to deception severity. DePaulo [24] suggests that descriptions of imagined events should contain fewer perceptual details, but a more recent meta-analysis revealed that the negative association between details and deception may be limited to handwritten accounts [61]. As people gain experience with constructing an extended, digital self or selves [62], they might also become more adept at burying their deception in rich, superfluous detail. With these insights, we reconcile some equivocal prior findings and assumptions about the use of detailed descriptions in CMC.

Furthermore, less self-deprecating and more flattering appear linguistic markers of business partners' deception severity. Compared with low levels, severely deceitful partners less frequently combined discrepancy words, such as "should" and "could," with first-person pronouns, and they more frequently combined achievement words, such as "earn" or "hero," with second-person pronouns. Regarding self-deprecating, DePaulo et al. [39] similarly suggest that deceivers refrain from it to avoid any implications of blame. Regarding flattering, our field study confirms Gordon's [63] laboratory experiments, in which he finds that linguistic elements of flattery and praise indicate severe deception. However, contrary to Fuller et al. (2009) as well as Schelleman-Offermans and Merckelbach [64], we did not find a negative relation between contextual embedding and deception in CMC by business partners. This speech act describes the spatial location and timely occurrence of an event; apparently, given the expectations in business communication, even severe deceivers cannot avoid contextualizing the place and time of the event that "entitled" them to request benefits. Even if partners aimed to deceive by imagining an event or borrowing from actual experience, it seems the time and place or the context in which the fabricated event occurred still needed to appear in their CMC to avoid negative expectancy violations [65, 66].

Beyond micro-level cues, we draw on conceptualizations of macro-level speech acts [34] to identify cohesiveness in message development as a first, higher-order linguistic predictor of deception severity in CMC. In our study, severely deceiving business partners structured their argumentation excessively, arguably to remove doubt and avoid detection. This finding is in line with DePaulo et al.'s [7] assertion that deceivers appear overly rehearsed, an impairment that seems exacerbated in highly motivated liars [44]. Our examination also highlights the importance of text structure as a macro-level speech act that allows for a more comprehensive understanding of cues of deception in CMC and supplements information system design for deception detection.

At the meta level, we profile deception in CMC by analyzing between-message interactional exchanges between business partners in a reward program. The degree of partners' linguistic style matching with the account manager's style was found to be a second higher-order, linguistic indicator of deception severity in CMC. DePaulo [67] demonstrates that deceivers are more concerned with their impression on others, a concern that is less present in truth tellers. Buller and Burgoon [21] propose that deceivers tend to mimic (what they perceive to be) receivers' behavior. Our approach, consistent with a speech act perspective, empirically validates that deceivers actively adapt their communication behavior through LSM to maximize their chances of success.

Limitations and Directions for Research

The limitations of our research reveal some avenues for further research. First, our examination of speech act cues of deception sought to aid a more holistic understanding of deception in CMC and provide a complementary, additive examination, at the expense of focusing on predictive accuracy. Although this type of model maximizes interpretation and meaning and yields direct estimates of predictor–outcome relationships, additional studies should seek to enhance predictive accuracy too. Further research might investigate theoretically unfounded linguistic cues of deception (see Table 1), transfer findings about other nonverbal cues to CMC [cf., 7], or include multiple tests to measure deception severity to increase predictive accuracy. Such studies may also further test the relation between the linguistic cues and the three deception dimensions, namely falsification, concealment, and equivocation [50].

Second, we derive linguistic markers to approximate speech acts, yet the scope of our study was limited to relatively anonymized CMC data. The significant overall explanatory power of the observed (e.g., work experience, gender, revenue, native language) and unobserved partner-level characteristics collectively explain 72% of variation in partners' inclination to write deceitful messages. They demonstrate the importance of accounting for partner-specific characteristics as relevant cues of deception in CMC. What remains to be investigated is what forces certain partners to deceive more. It appeals to intuition that partners should deceive more when they stand a chance of gaining more. Mazar, Amir, and Ariely [68] however find that deception does not increase with the amount of money involved. Relatedly, neither in our research nor in others [69] is there a relationship between the size of an account and deception. In other words, deception detection seems to go beyond the standard economic considerations of value of external payoff. Viable future research should aim to investigate such relationships. Although we control for English language ability, cross language difference and/or cultural differences and their relationship to deception severity or the perception thereof would complement such research designs [70], also given the global nature of business operations today. More understanding is also needed on the personal factors that make receivers more susceptibility to deceitful CMC [71].

Third, the study setting may have limited the generalizability of our findings. That is, we examined deception in a CMC-based system for managing a reward program. Other settings might not share the same specificities. For example, Anderson and Simester [72] suggest that fake reviews are widespread in consumer-to-consumer communication on online retail sites. The distinctive effects of communication in this, or other context, could offer interesting research opportunities related to integrity and deception detection.

Practical Implications

CMC systems have become the pervasive channel for most types of inter-organizational communication. Given the scope and scale of unstructured CMC and the natural human deficiency that limits their successful investigation, CIOs and IT managers need to mitigate the risks of severe deception in everyday business communications. Our proposed framework has important implications, which we outline below.

First, firms communicating and exchanging information and requests via CMC systems can use the linguistic cues for deception identified in this study and train managers to improve their intuitive skills for judging incoming e-mails. Such cue-based training has recently been shown to be very effective [6] and should better safeguard users by knowing how to detect the cues that leak from deceivers.

Second, managers should proactively implement systems to prevent deception in CMC. For example, the introduction of closed question forms (vs. open e-mail formats) give business partners basic decision rules to follow (e.g., identifying the actors involved), thus reducing their freedom to use deceitful formulations. Such system and interface changes promoting higher involvement and mutuality between managers and partners is likely to improve decision making and reduce deception due to increased rapport [73].

Third, we advocate a multilevel framework for designing systems to support deception detection through text analysis. While our study delineates and validates general linguistic cues at each of the three levels, the inclusion of partner level characteristics boosts the overall classification accuracy to 70% highlighting the importance of personal and context-specific cues. While this research does not offer insight into how to deal with deceivers, noting the time and resources necessary to manually investigate CMC in detail, our text analysis approach can help companies streamline their investigations and tailor their audits to messages which have been automatically pre-classified as potentially severely deceitful. Such information systems support rather than supplant managerial decision-making and would have to be carefully integrated to not threaten the human experts judging deception [74]

In conclusion, this study provides a better understanding of the linguistic markers of deception severity, spanning all three levels of CMC. This understanding may enable management to design information systems and provide employee training to safeguard against losses and risks in CMC. As a result, they can detect, deter, and prevent severe deception in business-to-business communication, and untangle any web of lies.

References

1. Levine, T.R. *Encyclopedia of Deception*. SAGE Publications, 2014.
2. Abbasi, A., and Chen, H. CyberGate: A Design Framework and System for Text Analysis of Computer-Mediated Communication. *MIS Quarterly*, 32, 4 (2008), 811-837.
3. Tassabehji, R., and Vakola, M. Business Email: The Killer Impact. *Communications of the ACM*, 48, 11 (2005), 64-70.
4. Herring, S.C. Computer-mediated communication on the Internet. *Annual review of information science and technology*, 36, 1 (2002), 109-168.
5. Buller, D.B., Burgoon, J.K., Daly, J., and Wiemann, J. Deception: Strategic and Nonstrategic Communication. *Strategic interpersonal communication* (1994), 191-223.
6. George, J.F., Biros, D.P., Burgoon, J.K., Nunamaker Jr., Jay F.; Crews, Janna M., Jinwei Cao, Marret, K., Adkins, M., Kruse, J., and Lin, M. The Role of E-training in Protecting Information Assets against Deception Attacks. *MIS Quarterly Executive*, 7, 2 (2008), 85-97.
7. DePaulo, B.M., Lindsay, J.J., Malone, B.E., Muhlenbruck, L., Charlton, K., and Cooper, H. Cues to deception. *Psychological bulletin*, 129, 1 (2003), 74.
8. Twitchell, D., Adkins, M., Nunamaker, J., and Burgoon, J. Using speech act theory to model conversations for automated classification and retrieval. *Proceedings of the International Working Conference Language Action Perspective Communication Modelling (LAP 2004)*, 2004, pp. 121-130.
9. Hancock, J., Curry, L., Goorha, S., and Woodworth, M. On lying and being lied to: A linguistic analysis of deception in computer-mediated communication. *Discourse Processes*, 45, 1 (2007), 1-23.
10. Matsumoto, D., and Hwang, H.C. Differences in Word Usage by Truth Tellers and Liars in Written Statements and an Investigative Interview After a Mock Crime. *Journal of Investigative Psychology and Offender Profiling* (2014).
11. Carlson, J.R., George, J.F., Burgoon, J.K., Adkins, M., and White, C.H. Deception in Computer-Mediated Communication. *Group Decision and Negotiation*, 13, 1 (2004), 5-28.
12. Austin, J.L. *How to do things with words: The William James Lectures delivered at Harvard University in 1955*. Oxford: Clarendon Press, 1962.
13. Searle, J. A classification of illocutionary acts. *Language in society*, 5, 01 (1976), 1-23.
14. Meibauer, J. Lying and falsely implicating. *Journal of Pragmatics*, 37, 9 (2005), 1373-1399.
15. van Dijk, T. *Text and context: Explorations in the semantics and pragmatics of discourse*. London: Longman, 1977.
16. Buller, D.B., Burgoon, J.K., White, C.H., and Ebesu, A.S. Interpersonal Deception Behavioral Profiles of Falsification, Equivocation, and Concealment. *Journal of Language and Social Psychology*, 13, 4 (1994), 366-395.
17. Zhou, L., Burgoon, J., Nunamaker, J., and Twitchell, D. Automating linguistics-based cues for detecting deception in text-based asynchronous computer-mediated communications. *Group decision and negotiation*, 13, 1 (2004), 81-106.
18. Kuechler, W.L., and Vaishnavi, V. So, Talk to Me: The Effect of Explicit Goals on the Comprehension of Business Process Narratives. *MIS Quarterly* (2006), 961-979.
19. Zhou, L., Burgoon, J.K., Twitchell, D.P., Qin, T., and Nunamaker Jr, J.F. A comparison of classification methods for predicting deception in computer-mediated communication. *Journal of Management Information Systems*, 20, 4 (2004), 139-166.
20. Goldkuhl, G. Conversational analysis as a theoretical foundation for language action approaches. *Proc of 8th Intl Working Conference on the Language Action Perspective*, 2003.

21. Buller, D., and Burgoon, J. Interpersonal deception theory. *Communication theory*, 6, 3 (1996), 203-242.
22. Ludwig, S., de Ruyter, K., Mahr, D., Wetzels, M., Bruggen, E., and De Ruyck, T. Take Their Word for It: The Symbolic Role of Linguistic Style Matches in User Communities. *MIS Quarterly*, 38, 4 (2014), 1201-1217.
23. Searle, J.R. *Speech acts: An essay in the philosophy of language*. Cambridge: Cambridge University Press, 1969.
24. Habermas, J. Reason and the Rationalization of Society, Volume 1 of The Theory of Communicative Action, English translation by Thomas McCarthy. Boston: Beacon Press (originally published in German in 1981), 1984.
25. Habermas, J. Theory of communicafive acfion Volume two: Liveworld and system: A crifique of funcfionalist reason, transl. Thomas A. McCarth y. Beacon Press, Boston, MA, 1987.
26. Biros, D.P., George, J.F., and Zmud, R.W. Inducing Sensitivity to Deception in Order to Improve Decision Making Performance: A Field Study. *MIS Quarterly* (2002), 119-144.
27. Toma, C.L., and Hancock, J.T. What lies beneath: The linguistic traces of deception in online dating profiles. *Journal of Communication*, 62, 1 (2012), 78-97.
28. Buller, D.B., and Burgoon, J.K. Interpersonal deception theory. *Communication theory*, 6, 3 (1996), 203-242.
29. Ekman, P., and Friesen, W. Nonverbal leakage and clues to deception. *Psychiatry*, 32, 1 (1969), 88-106.
30. Zuckerman, M., DePaulo, B., and Rosenthal, R. Verbal and nonverbal communication of deception. *Advances in experimental social psychology*, 14 (1981), 1-59.
31. Xiao, B., and Benbasat, I. Product-related Deception in E-commerce: a Theoretical Perspective. *MIS Quarterly*, 35, 1 (2011), 169-196.
32. Miller, G.R., and Stiff, J.B. *Deceptive communication*. Sage Publications, Inc, 1993.
33. Ekman, P. *Telling Lies: Clues to Deceit in the Marketplace, Politics, and Marriage (Revised Edition)*. WW Norton & Company, 2009.
34. Heracleous, L., and Marshak, R.J. Conceptualizing organizational discourse as situated symbolic action. *Human Relations*, 57, 10 (2004), 1285-1312.
35. Ireland, M.E., and Pennebaker, J.W. Language Style Matching in Writing: Synchrony in Essays, Correspondence, and Poetry. *Journal of Personality and Social Psychology*, 99, 3 (2010), 549-571.
36. Newman, M.L., Pennebaker, J.W., Berry, D.S., and Richards, J.M. Lying words: Predicting deception from linguistic styles. *Personality and social psychology bulletin*, 29, 5 (2003), 665-675.
37. Vrij, A., Edward, K., Roberts, K.P., and Bull, R. Detecting deceit via analysis of verbal and nonverbal behavior. *Journal of Nonverbal Behavior*, 24, 4 (2000), 239-263.
38. Zaparniuk, J., Yuille, J.C., and Taylor, S. Assessing the credibility of true and false statements. *International Journal of Law and Psychiatry*, 18, 3 (1995), 343-352.
39. DePaulo, B.M., LeMay, C.S., and Epstein, J.A. Effects of importance of success and expectations for success on effectiveness at deceiving. *Personality and social psychology bulletin*, 17, 1 (1991), 14-24.
40. Wolfe, J., and Powell, E. Biases in interpersonal communication: How engineering students perceive gender typical speech acts in teamwork. *Journal of Engineering Education*, 98, 1 (2009), 5-16.
41. Holmes, J. Paying compliments: A sex-preferential politeness strategy. *Journal of Pragmatics*, 12, 4 (1988), 445-465.
42. Hawkins, T.G., Pohlen, T.L., and Prybutok, V.R. Buyer Opportunism in Business-to-Business Exchange. *Industrial Marketing Management*, 42, 8 (2013), 1266-1278.

43. Kahai, S.S., and Cooper, R.B. The Effect of Computer-Mediated Communication on Agreement and Acceptance. *Journal of Management Information Systems*, 16, 1 (1999), 165-188.
44. DePaulo, B.M., Kirkendol, S.E., Tang, J., and O'Brien, T.P. The motivational impairment effect in the communication of deception: Replications and extensions. *Journal of Nonverbal Behavior*, 12, 3 (1988), 177-202.
45. Berger, J., and Milkman, K.L. What makes online content viral? *Journal of Marketing Research*, 49, 2 (2012), 192-205.
46. Raskin, D.C., and Esplin, P.W. Assessment of children's statements of sexual abuse. *The suggestibility of children's recollections* (1991), 153-164.
47. Campbell, M.K., Bernhardt, J.M., Waldmiller, M., Jackson, B., Potenziani, D., Weathers, B., and Demissie, S. Varying the Message Source in Computer-Tailored Nutrition Education. *Patient education and counseling*, 36, 2 (1999), 157-169.
48. Huffaker, D.A., Swaab, R., and Diermeier, D. The language of coalition formation in online multiparty negotiations. *Journal of Language and Social Psychology* (2010), 0261927X10387102.
49. Tausczik, Y.R., and Pennebaker, J.W. The Psychological Meaning of Words: LIWC and Computerized Text Analysis Methods. *Journal of Language and Social Psychology*, 29, 1 (2010), 24-54.
50. Burgoon, J.K., Buller, D.B., Guerrero, L.K., Afifi, W.A., and Feldman, C.M. Interpersonal deception: XII. Information management dimensions underlying deceptive and truthful messages. *Communications Monographs*, 63, 1 (1996), 50-69.
51. Cole, M.S., Bedeian, A.G., Hirschfeld, R.R., and Vogel, B. Dispersion-Composition Models in Multilevel Research. *Organizational Research Methods*, 14, 4 (2011), 718-734.
52. Hitsch, G.J., Hortaçsu, A., and Ariely, D. What makes you click: An empirical analysis of online dating. *2005 Meeting Papers*: Society for Economic Dynamics, 2005.
53. Granhag, P.A., Vrij, A., and Verschuere, B. *Detecting Deception: Current Challenges and Cognitive Approaches*. John Wiley & Sons, 2015.
54. Long, J.S., and Freese, J. *Regression models for categorical dependent variables using Stata*. Stata press, 2006.
55. Bliese, P.D., and Hanges, P.J. Being both too liberal and too conservative: The perils of treating grouped data as though they were independent. *Organizational Research Methods*, 7, 4 (2004), 400-417.
56. Algesheimer, R., Dholakia, U.M., and Herrmann, A. The Social Influence of Brand Community: Evidence from European Car Clubs. *Journal of Marketing*, 69, 3 (2005), 19-34.
57. Palan, A., Ref, R., and Tayob, Y. Partner Relationship Management Quick Start Tool. Accenture, 2009.
58. Klein, R., and Rai, A. Interfirm Strategic Information Flows in Logistics Supply Chain Relationships. *MIS Quarterly* (2009), 735-762.
59. Crosno, J.L., and Dahlstrom, R. A Meta-Analytic Review of Opportunism in Exchange Relationships. *Journal of the Academy of Marketing Science*, 36, 2 (2008), 191-201.
60. Aakhus, M., Ågerfalk, P.J., Lyytinen, K., and Te'eni, D. Symbolic Action Research in Information Systems: Introduction to the Special Issue. *MIS Quarterly*, 38, 4 (2014), 1187-1200.
61. Hauch, V., Blandón-Gitlin, I., Masip, J., and Sporer, S.L. Are Computers Effective Lie Detectors? A Meta-Analysis of Linguistic Cues to Deception. *Personality and social psychology Review* (2014), 1088868314556539.
62. Belk, R.W. Extended Self in a Digital World. *Journal of Consumer Research*, 40, 3 (2013), 477-500.

63. Krakora, D. Will Master be “as good as gold” for Cisco partners? , *PartnerPath*, 2014.
64. Schelleman-Offermans, K., and Merckelbach, H. Fantasy proneness as a confounder of verbal lie detection tools. *Journal of Investigative Psychology and Offender Profiling*, 7, 3 (2010), 247-260.
65. Van Laer, T., De Ruyter, K., Visconti, L.M., and Wetzels, M. The extended transportation-imagery model: A meta-analysis of the antecedents and consequences of consumers’ narrative transportation. *Journal of Consumer Research*, 40, 5 (2014), 797-817.
66. Jensen, M.L., Averbeck, J.M., Zhang, Z., and Wright, K.B. Credibility of Anonymous Online Product Reviews: A Language Expectancy Perspective. *Journal of Management Information Systems*, 30, 1 (2013), 293-324.
67. DePaulo, B.M. Nonverbal behavior and self-presentation. *Psychological bulletin*, 111, 2 (1992), 203.
68. Mazar, N., Amir, O., and Ariely, D. The dishonesty of honest people: A theory of self-concept maintenance. *Journal of Marketing Research*, 45, 6 (2008), 633-644.
69. Mazar, N., and Ariely, D. Dishonesty in everyday life and its policy implications. *Journal of Public Policy & Marketing*, 25, 1 (2006), 117-126.
70. Lewis, C., George, J., and Giordano, G. A cross-cultural comparison of computer-mediated deceptive communication. *PACIS 2009 Proceedings* (2009), 21.
71. Wright, R.T., and Marett, K. The Influence of Experiential and Dispositional Factors in Phishing: An Empirical Investigation of the Deceived. *Journal of Management Information Systems*, 27, 1 (2010), 273-303.
72. Anderson, E.T., and Simester, D.I. Reviews Without a Purchase: Low Ratings, Loyal Customers, and Deception. *Journal of Marketing Research*, 51, 3 (2014), 249-269.
73. Burgoon, J.K., Bonito, J.A., Bengtsson, B., Ramirez Jr, A., Dunbar, N.E., and Miczo, N. Testing the Interactivity Model: Communication Processes, Partner Assessments, and the Quality of Collaborative Work. *Journal of Management Information Systems*, 16, 3 (1999), 33-56.
74. Elkins, A.C., Dunbar, N.E., Adame, B., and Nunamaker, J.F. Are Users Threatened by Credibility Assessment Systems? *Journal of Management Information Systems*, 29, 4 (2013), 249-262.
75. Ali, M., and Levine, T. The language of truthful and deceptive denials and confessions. *Communication Reports*, 21, 2 (2008), 82-91.
76. Bond, G.D., and Lee, A.Y. Language of lies in prison: Linguistic classification of prisoners' truthful and deceptive natural language. *Applied Cognitive Psychology*, 19, 3 (2005), 313-329.
77. Brunet, M.K. Why Bullying Victims are Not Believed: Differentiating Between Children’s True and Fabricated Reports of Stressful and Non-stressful Events. University of Toronto, 2009.
78. Fuller, C.M., Biros, D.P., and Wilson, R.L. Decision support for determining veracity via linguistic-based cues. *Decision Support Systems*, 46, 3 (2009), 695-703.
79. Humpherys, S.L., Moffitt, K.C., Burns, M.B., Burgoon, J.K., and Felix, W.F. Identification of fraudulent financial statements using linguistic credibility analysis. *Decision Support Systems*, 50, 3 (2011), 585-594.
80. Porter, S., and Yuille, J.C. The language of deceit: An investigation of the verbal clues to deception in the interrogation context. *Law and Human Behavior*, 20, 4 (1996), 443.
81. Zhou, L., and Zenebe, A. Representation and Reasoning under Uncertainty in Deception Detection: A Neuro-fuzzy Approach. *Fuzzy Systems, IEEE Transactions*, 16, 2 (2008), 442-454.

82. Derrick, D.C., Meservy, T.O., Jenkins, J.L., Burgoon, J.K., and Nunamaker Jr, J.F. Detecting deceptive chat-based communication using typing behavior and message cues. *ACM Transactions on Management Information Systems (TMIS)*, 4, 2 (2013), 9.
83. Pak, J., and Zhou, L. Social structural behavior of deception in computer-mediated communication. *Decision Support Systems*, 63 (2014), 95-103.
84. Braun, M.T., and Van Swol, L.M. Justifications Offered, Questions Asked, and Linguistic Patterns in Deceptive and Truthful Monetary Interactions. *Group decision and negotiation* (2015), 1-21.
85. Zhou, L., Burgoon, J.K., Zhang, D., and Nunamaker, J.F. Language dominance in interpersonal deception in computer-mediated communication. *Computers in Human Behavior*, 20, 3 (2004), 381-402.

Table 1. Relevant Studies

Article	Micro-Level Cues	Context	Incentive	Medium
Ali and Levine [75]	**Fewer negative emotions, less discrepancy, fewer modal verbs, more modifiers, longer speech**	Confessions or lies about trivia game cheating	US$20	Video
Anderson and Simester [72]	**More words, word length, family references, repeated exclamation points**	Reviewers writing product reviews that are confirmed and not confirmed to have purchased the product.	No reward	CMC
Bond and Lee [76]	**More third-person pronouns, more motion words, more spatial words, fewer sensory-perceptual words,** fewer first-person pronouns, more negative emotion words, more motion verbs, fewer exclusive words	Eyewitness recollections or lies about crime-related video segments	Group Pizza Party	Audio
Brunet [77]	**Fewer words, more motion terms, more self-references,** fewer spatial terms, fewer sensory and perceptual process words, fewer tentative words	True or fabricated stories about sporting or bullying events	US$10	Video
Fuller, Biros, and Wilson [78]	**More words, fewer sensory words, less lexical diversity, more non–self-references, more second-person pronouns, more other references, more group pronouns, fewer spatial terms,** more affect	Real-life true or false military misconduct witness statements	(non-) judicial punishment	Written statement
Hancock et al. [9]	**More words, more questions, more third-person pronouns, fewer causation terms, more sense terms,** fewer first-person pronouns, more second-person pronouns, more negative affect terms, fewer exclusive words and negation terms	Truths or lies about various conversation topics, such as “Discuss the most significant person in your life”	Course credit	CMC
Humpherys et al. [79]	**More affect, greater complexity, less diversity, more non-immediacy, more words,** more expressivity, less specificity, less uncertainty	Real-life non-fraudulent or fraudulent financial statements		Report (10-k)
Matsumoto and Hwang [10]	**More sensory and perceptual process words, fewer positive emotion words, more negation words, fewer tentative words, more time-related words, more total words used, more motion verbs, less self-referent and other referents**	Truthful or false alibis about a mock theft	US$100	Written statement
Newman et al. [36]	**Fewer first-person pronouns, fewer third-person pronouns, more negative emotion words, more motion verbs, fewer exclusive words**	Truthful and deceitful essays about views on abortion	No reward	Written statement
Porter and Yuille [80]	**Less details, less coherence, less admitting lack of memory**	Truthful or false alibis about a mock theft	US$5	Audio
Schelleman-Offermans and Merckelbach [64]	**Less contextual embedding, less attribution of the perpetrator’s state, fewer exclusive words,** fewer relevant details, fewer descriptions of interactions, less reproductions of speech, fewer unusual details, more superfluous details, fewer referrals to own subjective experience, fewer motion words, more self-referencing, fewer negative emotion words	True and fabricated stories about an aversive situation in which the participant had been the victim	No reward	Written statement

Zhou et al. [19]	**More sentences and words, less lexical and content diversity, more modifiers, more positive affect, more negative affect, more group references, less plausibility**, less self-referencing, fewer redundancies, fewer spatial words, and fewer perceptual references.	Truthful or deceitful communication about solving the Desert Survival Problem	Course credit	CMC
Zhou et al. [17]	**More pleasantness, more imagery**	Truthful or deceitful communication about solving the Desert Survival Problem	Course credit	CMC
Zhou and Zenebe [81]	**More modal verbs, more group references, more misspelled words, more modifier verbs, more affect, less word diversity, less causality**	Truthful or deceitful communication about a mock theft as well as about solving the Desert Survival Problem	Course credit	Audio and CMC
Derrick, et al. [82]	**Fewer words, more edits,** less lexical diversity	Truthful or deceitful communication about descriptions, affect, narratives, personality, moral dilemmas, comparisons, attitudes, and future actions	Course credit	CMC
Pak and Zhou [83]	**More references, more substitutions, more ellipses, more conjunctions, more lexical cohesion**	Deception to win the mafia game		CMC
Braun and Van Swol [84]	**More negations,** fewer words, more questions, fewer negative emotions words, fewer first-person pronouns, fewer third-person pronouns	Truthful or deceitful communication with a monetary negotiation game	Course credit	CMC
Toma and Hancock [27]	**Fewer words, fewer first-person pronouns, more negations, less negative emotions**	Truthful or deceitful communication about online dating	US$30	CMC
Zhou, et al. [85]	**Fewer words, less subjunctive language, nonlinear change in uncertainty, more expressivity, less negative affect, nonlinear change in intensity,** more positive affect	Truthful or deceitful communication about solving the Desert Survival Problem	Course credit	CMC

Notes: Variables that produced significant results in the respective study appear in bold. Unless otherwise indicated, the studies were conducted in a laboratory-based, experimental, comparison setting.

Table 2. Cues of Deception Severity: Linguistic Inquiry and Word Count (LIWC) Operationalization and Representative Words

Speech Act Cue	LIWC Categories	Representative Words	Words in Category
Micro-level			
Referencing	Personal pronouns	we, them, her	70
Embedding	Relativity words	area, down, until	638
Detailing	Adjectives	sublime, brilliant, peerless	1,656
Self-deprecating	First-person singular pronouns with	I, me, mine;	12
	discrepancy words	should, would, could	76
Flattering	Second-person pronouns with	you, your, thou;	20
	achievement words	earn, hero, win	186
Macro-level			
Structuring	Cognitive process words	cause, know, ought	730
Meta-level			
LSM	Function words	an, am, to	464

Notes: The word categories were all adopted from the LIWC text-mining dictionaries, with the exception of the adjectives. The research team compiled the list of 1,656 adjectives, using the following online sites: enchantedlearning.com, the Oxford dictionary, thesaurus.com, and yourdictionary.com. Text mining was conducted using the 2007 Linguistic Inquiry and Word Count program and the tm Package in R.

Table 3. Non-Standardized Descriptive Statistics and Correlations

	M	**(SD)**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Request-level variables																
1. DeceptionSeverity$_r$	1.72	(1.01)	1.00													
2. Referencing$_r$	9.50	(5.11)	-.15**													
3. Contextual Embedding$_r$	1.26	(5.75)	.02	-.06**												
4. Detailing$_r$	11.70	(6.55)	.12**	-.15**	.21**											
5. Self-deprecating$_r$	.31	(.52)	-.06**	.20**	.04	-.02										
6. Flattering$_r$	.32	(.54)	.06**	.01	.03	.05**	.24**									
7. Structuring$_r$	38.52	(5.53)	.13**	-.02	.03	-.02	-.02	-.02								
8. LSM$_r$	.46	(.28)	.06*	.07*	.04	.04	.13**	.14**	-.03							
9. Signature$_r$	.51	(.48)	-.02	-.01	-.06**	-.03	.03	.04	.01	.01						
10. Unanswered Question$_r$	.02	(.13)	.14**	.01	.01	.01	.01	.06**	-.01	.03	.01					
11. Monetary Amount$_r$	1373,19	(2574,83)	-.05	.02	-.02	.05	.02	.06	-.02	-.05	.02	.06				
Partner-level variables																
12. Experience$_p$	12.53	(7.17)	-.16**	-.01	.02	-.09**	-.08**	-.02	-.05	.03	.05	.01	.14**			
13. Sex$_p$	.25	(.43)	-.11**	.04	-.04	-.05	-.03	.02	-.03	-.03	.07**	.02	.09	-.02		
14. NativeSpeaker$_p$	0,84	(.37)	.19**	-.06**	.05*	.07**	-.04	.01	.15**	-.03	-.04*	.01	-.09**	-.06*	.06*	
15. AccountSize$_p$	2179,23	(4394,97)	-.06	.1	-.15*	-.05	-.03	.09	-.02	-.07	-.17*	.14	-.13	-.25*	-.14	.14

Notes: * $p < .05$. ** $p < .01$.

Table 4. Multilevel Regression Analysis

Variables	Model 0	Model 1 Estimate (SE)	Model 1 Odds Ratio	Model 2 Estimate (SE)	Model 2 Odds Ratio	Model 3 Estimate (SE)	Model 3 Odds Ratio
Request-level variables							
Referencing$_r$		-.31** (.07)	.73	-.31** (.07)	.73	-.32** (.07)	.72
Contextual Embedding$_r$		-.09 (.07)	.92	-.09 (.07)	.91	-.09 (.07)	.91
Detailing$_r$		.13* (.07)	1.13	.13* (.07)	1.17	.13 * (.07)	1.14
Self-deprecating$_r$		-.15** (.08)	.86	-.16** (.08)	.85	-.17** (.08)	.84
Flattering$_r$		.18** (.07)	1.19	.19** (.07)	1.20	.17** (.07)	1.18
Structuring$_r$				.34** (.12)	1.41	.35** (.12)	1.41
LSM$_r$						.26** (.09)	1.30
Signature$_r$		.20 (.15)	1.21	.21 (.15)	1.22	.21 (.15)	1.24
Unanswered Question$_r$		.25** (.06)	2.47	.25** (.06)	1.29	.26** (.06)	1.29
Monetary Amount$_r$		-.28 (.17)	.75	-.28 (.17)	.75	-.27 (.17)	.76
Partner-level variables							
Experience$_p$		-.51** (.15)	.59	-.52** (.15)	.59	-.55** (.15)	.58
Sex$_p$		-.70* (.35)	.49	-.70* (.35)	.49	-.76* (.35)	.46
NativeSpeaker$_p$		.90** (.11)	2.47	.89** (.11)	2.45	.90** (.11)	2.46
AccountSize$_p$		-.33 (.26)	.71	-.33 (.26)	.72	-.30 (.27)	.73
Log likelihood	2406.29	2296.78		2292.36		2286.49	
AIC	4822.58	4643.41		4638.71		4630.98	
N (requests)	2420	2420		2420		2420	
N (channel partners)	1320	1320		1320		1320	

Notes: All coefficients are standardized. Odds ratio (OR) = the odds of a one-unit increase in deception severity, given a one-unit increase in the explanatory variable, *ceteris paribus*. For Models 0–3, the LR test is significant (*p* < .01), indicating a relative increase in model fit. The estimates for D_{M1}-D_{M4}, D_c and D_p are not reported, because they do not offer any interpretative relevance. Importantly none of the account managers' dummy variables (D_{M1}-D_{M4}) were significant, so there was no systematic difference in their rating of deception severity.
* *p* < .05. ** *p* < .01.