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The Location of Maximum Emotion in Deceptive and Truthful Texts

Amir Sepehri[1], David M. Markowitz[2], and Rod Duclos[1]

Abstract

Meta-analytic evidence suggests that verbal patterns of emotion betray deceit, but it is presently unclear whether the location of maximum emotion in lies and truths matters to reveal deception. We contribute to the deception literature by offering analyses at the sentence level to locate where emotion is most pronounced in deceptive versus truthful texts. Using two public data sets—news articles (Study 1) and hotel reviews (Study 2)—we found that maximum emotion occurs toward the beginning of deceptive texts while maximum emotion appears later for truthful texts. In addition to demonstrating the effect across diverse settings, we used two different measurements for emotion and separated the results by valence, replicating the maximum emotion effect each time. The predictive nature of maximum affect ranged from 54% to 56% across data sets, a rate consistent with most deception studies using 50-50 lie–truth base rates. Implications for future research and deception theory are discussed.

Keywords

language, emotion, persuasion, research methods, communication

Early research by Ekman and colleagues popularized the study of emotion as a lens into deception phenomena through the leakage hypothesis (Ekman & Friesen, 1969). Here, liars try to conceal their deception but fail to fully accomplish this goal. Deception clues (e.g., pupil dilation) indicate that a person is lying, and leakage via another nonverbal marker indicates what the person is lying about. Despite the popularity of leakage hypothesis, large-scale evidence supporting the idea that nonverbals reveal social and psychological phenomena, such as deception, is less clear and often mixed (Barrett et al., 2019; C. F. Bond & DePaulo, 2006; DePaulo et al., 2003; Hartwig & Bond, 2014; Levine, 2020). Therefore, deception researchers have recently turned to other forms of communication behavior that might be relevant to understand how people lie with emotion (Vrij, 2019).

Language patterns have become a focus in deception research because words have small- to medium-sized associations with dishonesty (Hauch et al., 2015), and the methods to evaluate word patterns at scale have become mainstream (Boyd & Pennebaker, 2015). Indeed, liars display more verbal negative emotion than truth-tellers (Hauch et al., 2015), though typical evaluations treat emotion as a monolithic measure (e.g., the overall rate of positive or negative affect across false and truthful speeches; Ali & Levine, 2008; G. D. Bond & Lee, 2005; Hancock et al., 2007; Markowitz & Griffin, 2020; Newman et al., 2003). In the current article, we contribute a new approach to the study of emotion in verbal deception by evaluating how the location of emotion differs between lies and truths. Using a diverse set of public and published data, we explore the peak or maximum location of emotion as it appears in false and truthful discourse at the sentence level. Our results indicate that deceptive speech tends to front-load emotion, as the greatest rate of affect appears earlier in false compared to truthful communication patterns.

Deception and Language: A Context-Contingent Enterprise

Theories of deception and language argue that the expression of emotion is a crucial component of the lying and truth-telling experience. The Contextual Organization of Language and Deception (COLD) framework (Markowitz & Hancock, 2019), for example, argues that the emotional experience of a liar matters because affect can indicate what the speaker is thinking and feeling in the moment of their deception. Recall, a particular type of emotional response, namely negative affect, has received substantial attention as a result of theories that propose liars are more anxious, guilt-ridden, and distressed during their speech acts compared to truth-tellers (Ekman, 2001; Zuckerman et al., 1981). Evidence in support of this

[1] Ivey Business School, Western University, London, Ontario, Canada
[2] School of Journalism and Communication, University of Oregon, Eugene, OR, USA

Corresponding Author:
Amir Sepehri, Ivey Business School, Western University, 1255 Western Rd., London, Ontario, Canada N6A 3K7.
Email: asepehri.phd@ivey.ca

proposition is weak at the meta-analytic level, however (Hauch et al., 2015), which is reasonable given the mixed primary study evidence (Ali & Levine, 2008; Burns & Moffitt, 2014; Markowitz & Griffin, 2020; Newman et al., 2003; Toma & Hancock, 2012). Therefore, the relationship between deception and emotion to reveal psychological dynamics is not invariably uniform but instead affected by contextual constraints (Gerlach et al., 2019; Levine, 2020; Markowitz & Hancock, 2019).

Contextual constraints that impact the relationship between deception and language include genre conventions (Markowitz & Hancock, 2019). Language patterns are flexible and often reflect shifts in a person's discourse community (Biber et al., 2007). For example, people speak to their academic advisor differently from how they speak to their significant other. Since conventions shift across discourse communities, a person's verbal output should change as well. Liars are susceptible to these constraints because deception occurs across a diversity of settings. If a setting does not contain a high rate of pronouns or self-references (e.g., scientific writing; Markowitz & Hancock, 2014, 2016), we should not expect such measures and their associated psychological correlates to matter for deception compared to a setting where such language patterns are normative (e.g., blogs, social media). Together, discourse communities modify the language patterns that are possible and probable in a person's discourse (Markowitz & Hancock, 2019).

The Current Investigation

Given that affect matters, but is context-contingent for deception, it is important to consider new ways of evaluating emotion and its relationship to dishonesty. In this article, we draw on prior deception theories and evidence by starting with the baseline assumption that deception modifies emotion but not uniformly across settings (Hauch et al., 2015; Levine, 2014, 2020; Markowitz & Hancock, 2019; McCornack et al., 2014). We are less interested in whether deception affects emotional responses than in the location of emotion in honest and dishonest discourse. Such data could provide important evidence for deception detection and betray psychological experiences when lying.

There is a good reason to suspect that the location of maximum emotion is different across false and truthful speech based on recent evidence documenting how often people produce daily lies. Lie production research suggests that prevalence (e.g., how much people report lying on an average day) is not normally distributed across the population. For example, most people are honest, and only a few people are prolific liars within a population; they tell a disproportionate number of falsehoods compared to others (Halevy et al., 2014; Markowitz & Hancock, 2018; Serota & Levine, 2014; Serota et al., 2010). Since lying rates are not normally distributed, it is reasonable that other lie production dynamics, such as the peak location of emotion in a person's speech, should not be evenly distributed as well.

This expectation is also reasonable based on recent work evaluating the placement of lies embedded within truthful disclosures. Research by Leal and colleagues (2016) had participants complete an online insurance claim of eight items, and they could freely make honest or dishonest claims. The authors located where participants made their first fake claim, and on average, the first fake was located in the third position out of eight (Leal et al., 2016). In another paper, Deeb and colleagues (2020) evaluated the location of lies and truths in interviews across those from high- and low-context cultures. The results generally suggested that people told lies toward the end of an interview, presumably to prepare for their deception and gauge the responsiveness of the interviewer (Deeb et al., 2020). Those who lied at the beginning of an interview suggested that this strategy might have been unexpected by the interviewer or to simply "be done with the lie" (Deeb et al., 2020, p. 13).

Taken together, the location and placement of lies matters, but research has not focused on the location of maximum emotion within false and truthful disclosures at the language or sentence level. Limited work has evaluated the order of deceptive and truthful statements to assess how communicators varied verbal and nonverbal displays (Burgoon et al., 1999), though evidence evaluating the location of peak emotion related to veracity is scarce.

We believe that evaluating the emotional peak of deception has important implications for lie production and lie detection. Most lie production scholars evaluate mean differences between lies and truths for an emotion measure (e.g., negative affect, positive affect). Such differences only offer descriptive information about the potential psychological processes involved in lying and truth-telling for a particular setting. However, as prior evidence and theory suggest, emotion effects in deception research are often small, mixed, and affected by context-dependent moderators (Hauch et al., 2015; Levine, 2020; Markowitz & Hancock, 2019). Therefore, we attempt to provide evidence that cuts across deception settings to indicate where the greatest rate of emotion appears in lies and truths.

The location of maximum emotion also has important implications for deception detection. One method of deception detection, scientific content analysis (SCAN), operates by an individual revealing all relevant information about an event and evaluators hand-code aspects of a statement to betray lies or truths. Evaluators look for aspects of a statement that might reveal deception, such as spontaneous corrections or the sequence of information (for a full list of SCAN criteria, see Nahari et al., 2012). One SCAN criterion, the location of emotions, is particularly relevant for the current investigation. SCAN predicts liars place emotion before a story's apex, but truth-tellers distribute emotion more evenly throughout a story. Despite its application in law enforcement and forensic settings, SCAN has little empirical support (Bogaard et al., 2014, 2016). We evaluate how a variant of this SCAN criterion, the location of *maximum* emotion at the language level, might reveal deception in a nonforensic setting with automated approaches.

Table 1. Descriptive Statistics Across Data Sets.

			Word Count						Sentence Count				
Data Set	Veracity	*n*	*M*	*SD*	*Q1*	*Q2*	*Q3*	*M*	*SD*	*Q1*	*Q2*	*Q3*
News	Fake	16,669	453.13	326.85	309	396	525	20.91	14.37	13	18	25
	Real	19,727	403.94	270.15	192	376	542	16.26	11.36	8	15	22
Hotel reviews	Fake	796	147.75	84.90	89	125.5	183	9.14	4.79	6	8	11
	Real	788	152.70	90.43	90	131	185	10.45	6.06	6	9	13

Other deception detection methods also suggest the evaluation of maximum affect in deception is reasonable. Criteria-based content analysis (Koühnken & Steller, 1988) evaluates the logic, structure, and information offered by details in a person's statement to indicate deception (Amado et al., 2015; Vrij, 2005). One aspect of this approach argues that liars use fewer details to describe a scene or event compared to truth-tellers because they are creating an account from fantasy (Vrij, 2019). Criteria-based content analysis is also consistent with a theory and technique called reality monitoring (Johnson & Raye, 1981), where the details in a statement often reveal liars compared to truth-tellers (Masip et al., 2005). Both approaches predict that the number and types of details matter to reveal false versus truthful statements (Vrij, 2018) but fail to account for *where* these statements might be placed and specifically where emotion is located. Evidence revealing where people place peak emotion in lies relative to truths might benefit law enforcement or other stakeholders who often attempt to detect deception but fail to achieve better-than-chance accuracy with 50-50 lie–truth base rates (C. F. Bond & DePaulo, 2006; Levine, 2020).

We explore where peak emotion is located across lies and truths using published and public data sets. Since this is one of the first articles to address the peak location of emotion in false and truthful speech with automated methods, we pose the following research question:

> **Research Question:** Where is the peak of emotion located in false and truth speech?

While we are interested in locating maximum emotion in deceptive and truthful texts, prior social psychological evidence suggests that the perceived intensity of emotion tends to appear at the beginning and end of an experience (Kahneman et al., 1993; Redelmeier & Kahneman, 1996). This "peak-end" heuristic suggests that an experience is not perceived uniformly or monolithically but rather as discrete moments that stand to represent general feelings toward the experience (Kahneman & Tversky, 1972). We seek to extend the "peak-end" heuristic by evaluating verbal behavior and its location in false and truthful statements, instead of relying on perceptions.

To evaluate the prior research question, we collected data from two archives that contained deceptive and truthful texts. Our first study included fake and real news articles (Ahmed et al., 2017, 2018). The second study included fake and real hotel reviews, also collected from prior work (Ott et al., 2011). We chose these data sets due to their topical relevance to the research question (e.g., texts that contain clear veracity markers) and several consistencies across data sets. For example, both data sets contain nonspoken texts, and the writers presumably have consistent pragmatic goals (e.g., trying to convince a reader of an experience or event that happened in reality or was fabricated; Markowitz & Hancock, 2019). The genre conventions are arguably dissimilar across data sets, however, which also motivated their selection. The norms of news writing (e.g., formal and analytic style, reporting on evidence) are inherently different than the norms of writing a hotel review (e.g., narrative style, reporting on experience), and the presumed audiences are different as well. We evaluate whether the location of peak emotion in false and truthful texts has a similar pattern across settings with divergent discourse communities (Biber et al., 2007). Descriptive information for each data set is located in Table 1. All data sets are located on the Open Science Framework (https://osf.io/fuzp6).

Study 1

Method

Data Set Information

We obtained a data set of 36,396 unique news articles used in prior work (Ahmed et al., 2017, 2018). Ground truth was established by Ahmed and colleagues in the following manner: Real news articles were collected from Reuters.com, and fake news articles were collected from untrustworthy websites flagged by PolitiFact, who collaborated with Facebook to identify deceptive material on their platform. PolitiFact (2017) identified four categories of untrustworthy websites that "peddle bogus stories," and "it's not always apparent to readers that's the case": (1) parody sites, (2) news imposter sites, (3) fake news sites, and (4) sites with a mix of truthful and fake news. While the exact categorization procedure is not public, sites in the fake news collection are deceptive while those collected from Reuters are not.

All articles were topically related to political and international news, and texts were labeled fake or real. Note, we excluded texts that contained fewer than three sentences, a threshold consistent with prior work that considers sentence-level analyses in natural language processing (Ludwig et al., 2014; van Laer et al., 2019). The total number of sentences evaluated in this data set is 669,223 sentences.

Text Analysis Procedure

All texts were evaluated with Linguistic Inquiry and Word Count (LIWC) to obtain overall text-level scores. Then, each text was segmented at the sentence level (using sentence identifiers such as ".", "!", or "?"). Therefore, the unit of analysis was each individual sentence per text (per data set). For each sentence, we calculated the total rate of affect using LIWC (Pennebaker et al., 2015). In other words, the data were segmented into sentences and received individual LIWC scores.

LIWC is a dictionary-based text analysis software that counts words from a piece of text as a percentage of the total word count. It increments an internal dictionary of dimensions related to social (e.g., words related to friends, family), psychological (e.g., words related to emotion, cognitive processing), and part of speech categories (e.g., pronouns, articles, prepositions). LIWC's approach has been validated to quantify word patterns for spoken and written text (Tausczik & Pennebaker, 2010), with hundreds of studies using this tool for social and psychological evaluations of language data (Humphreys & Wang, 2018). It is often a primary tool to evaluate word patterns in deception research as well (Hauch et al., 2015; Markowitz & Griffin, 2020; Markowitz & Hancock, 2016; Newman et al., 2003).

Consistent with our research aim, we then determined the sentence that contained the maximum level of affect (from LIWC) within each text. We divided the corresponding sentence number by the total number of sentences in each text, which provided us with a measure and location of maximum affect relative to the entire text. Smaller numbers indicate that maximum affect is located toward the beginning of the text, and larger numbers indicate that maximum affect is located toward the end of the text. For example, if maximum affect occurs in the fourth sentence in a 10-sentence text, the maximum affect score will be .40. However, if maximum affect occurs in the ninth sentence of a 10-sentence text, the value will be .90. We henceforth call this dependent measure the *maximum affect score*, and article type (deceptive vs. truthful text) was our independent variable across studies.

Results and Discussion

We used nonparametric Mann–Whitney U tests to determine maximum affect differences between fake and truthful texts because the maximum affect scores were not normally distributed. Parametric tests are offered in the Supplementary Materials for transparency and produced substantively equivalent results.

The maximum affect score for fake news (mean rank = 17,197.88) was significantly lower than the maximum affect score for real news (mean rank = 19,044), $U = 147{,}735{,}424$, $z = -16.71$, $p < .001$, $\eta^2 = .008$. We also ran the analyses on the negative and positive emotion scores separately. The results were consistent, where maximum positive, U = 151,792,354, z = −12.64, $p < .001$, $\eta^2 = .004$, and negative affect, $U = 156{,}591{,}879$, $z = -7.84$, $p < .001$, $\eta^2 = .002$, occurred more toward the beginning of the text in fake news than real news.

Together, maximum affect tends to occur earlier in fake news than real news. Since Study 1 is a relatively novel approach identifying the location of maximum affect in deceptive and truthful texts, we attempted to replicate these results in another publicly available data set with different genre conventions. This replication effort, using hotel reviews from Tripadvisor, helps to assess the validity of the analytic method to indicate deception.

Study 2

Method

Fake and real hotel reviews were obtained from prior work (Ott et al., 2011). This data set contains 800 fake and real reviews from Tripadvisor and is often considered a gold-standard archive for fake review detection. Ground truth was established by paying people to write fake reviews and eliminating reviews from first-time reviewers, non-English reviews, reviews that had less than a five-star rating, and reviews with fewer than 150 characters. Drawing on prior work, Ott and colleagues (2011) suggest these characteristics betray deceptive opinion spam relative to truthful opinions, and their elimination created the truthful review collection. Note, the number of reviews retained in our analyses were slightly smaller than the original paper due to analytic conventions for this study (e.g., excluding texts that contained fewer than three sentences). The total number of sentences evaluated in this data set is 15,510 sentences.

Results

The maximum affect score for deceptive reviews (mean rank = 766.58) was significantly lower than the score for truthful counterparts (mean rank = 818.69), U = 292,989.50, z = −2.27, $p = .023$, $\eta^2 = .003$. The results were consistent by valence, where maximum positive, U = 295,110, z = −2.04, $p = .042$, $\eta^2 = .003$, and negative affect, U = 283,186, z = −3.35, $p = .001$, $\eta^2 = .007$, occurred toward the beginning of fake versus real reviews.

Robustness Checks Across Studies

Combined effects. We combined the data sets into one analysis to evaluate whether similar patterns emerged when combining genres. Indeed, a consistent effect emerged as the maximum affect score for deceptive text (mean rank = 17,963.93) was significantly lower than the maximum affect score for truthful text (mean rank = 19,864.45), U = 161,218,235, z = −16.84, $p < .001$, $\eta^2 = .007$. Positive and negative affect showed consistent effects (ps < .001, η^2s < .004).

Emotional intensity. We also explored how using other text analysis tools might impact our results to ensure they were not a LIWC artifact. We replaced LIWC with the R package

Table 2. Results for the Leave-One-Out Cross-Validated Model.

	Hit	Miss	Hit Rate (%)	Accuracy (%)
Study 1: News				
Fake (n = 16,669)	4,274	12,395	25.6	55.8
Real (n = 19,727)	16,026	3,701	81.2	
Study 2: Hotel reviews				
Fake (n = 796)	441	355	55.4	53.5
Real (n = 788)	407	381	51.6	
Combined effects				
Fake (n = 17,465)	4,615	12,850	26.4	55.6
Real (n = 20,515)	16,483	4,032	80.3	

sentimentr (Version 2.7.1), which accounts for verbal emotional intensity (Rinker, 2019). For example, the phrases "I am happy" and "I am extremely happy" would be scored with the same intensity of positive emotion in LIWC, but the sentimentr package accounts for the verbal intensifier (e.g., *extremely*), indicating a more extreme positive emotion than happy alone. Note, since sentimentr provides bipolar emotionality scores (high scores are positive and low scores are negative), we converted all scores to their absolute values in order to detect the sentence carrying maximum emotionality, which mirrors the scores provided by LIWC's *affect* category.

Using sentimentr scores, we found a consistent pattern of results relative to LIWC, with similar levels of significance and effect sizes in both studies. In the news data set, the maximum sentiment score for fake news (mean rank = 17,124.33) was significantly lower than the maximum sentiment score for real counterparts (mean rank = 19,106.16), U = 146,509,302, z = −17.94, $p < .001$, $\eta^2 = .009$. Similarly, in the hotel reviews data set, the maximum sentiment score for fake reviews occurred earlier (mean rank = 767.24) than real reviews (mean rank = 818.01), U = 293,520.50, z = −2.21, $p = .027$, $\eta^2 =$ .003.

Taken together, across two studies using data from different empirical settings and different measures of emotion, we consistently find that maximum affect tends to occur toward the beginning for deceptive texts but not for truthful texts.

Statistical Classification

Using leave-one-out cross-validated models, with weighted prior probabilities, we assessed the ability to use the location of maximum affect to detect deception statistically. The results in Table 2 suggest that deceptive (fake) and truthful (real) texts were discriminated with near 56% accuracy. The accuracy for real news was substantially better than the accuracy for fake news, though the accuracy differences for fake and real reviews were not as stark. Note, consistent results or slight improvements in overall accuracy were obtained by adding positive and negative affect as predictors to the leave-one-out models. While these accuracies are limited forensically, they are consistent with those in deception research that use near 50-50 base rates of lies and truths (C. F. Bond & DePaulo, 2006; Levine, 2020; Markowitz & Hancock, 2016).

General Discussion

The results from this article suggest that rates of maximum affect tend to occur more toward the beginning of deceptive texts and more downstream for truthful texts. We find the same pattern of results when affect is divided into its positive and negative components. While previous researchers have examined the overall rate of emotion to describe false and truthful communication patterns, we observed that the location of peak emotionality is a theoretically important albeit forensically constrained indicator of deception due to low detection accuracy.

This is one of the first studies to evaluate where maximum affect is placed in false and truthful discourse, and our analytic approach is one that can be applied to a range of texts. Crucially, we explored the maximum affect effect in two distinct settings. News and hotel reviews are inherently different in terms of information consumption processes, the purpose of communication, and length, for example. Despite their differences, we find a similar pattern of results across both settings, which underscores the robustness of our findings. The effects also emerged after using two different approaches to measure affect. LIWC is a gold-standard program for dictionary-based text analyses, though accounting for emotional intensity via sentimentr also produced a consistent pattern of results. We believe our approaches broaden the tool kit for researchers who seek to evaluate emotion holistically and demonstrate the robustness of the maximum emotion effect to multiple levels of text analysis.

Our results make several contributions to deception research. First, many deception scholars have examined the mean values of emotion across false and truthful groups. We offer evidence that the location of maximum emotion in deceptive and truthful texts is dissimilar at the sentence level. Most of the extant research has focused on word-level insights for deception production and detection. We believe that a sentence-level approach can augment and further clarify how deception affects language patterns (see Büschken & Allenby, 2016).

Second, we extend deception theory, particularly the COLD framework (Markowitz & Hancock, 2019), which suggests that psychological dynamics are crucial to evaluate how liars and truth-tellers communicate. The COLD framework does not make assumptions about the location of maximum affect in false and truthful texts, but that affect tends to be an important component of deception. Therefore, this study offers a nuanced perspective of the relationship between deception, language, and emotion. Deception modifies emotion but not uniformly throughout a person's writing style. Therefore, psychological dynamics revealed through the location of emotion in language are nonuniform in lies versus truths as well. Emotion processes remain important to understand deception, though our evidence suggests the placement of affect should also be considered for a holistic evaluation of how people psychologically respond when communicating false and truthful speech.

Deception detection methods were also extended in this article by using the location of maximum affect approach. Recall, empirical evidence supporting SCAN is scarce, though our work suggests the location of maximum of emotion might be an important nuance to the SCAN approach. SCAN largely considers the location of emotion in false and truthful text, but our work determined that the location of maximum emotion can help to betray deceit. We provide evidence to demonstrate that SCAN-like criteria can assist in discriminating lies and truths, though detection accuracy from this approach is clearly limited (Table 2). Prior criteria-based content analysis (Koühnken & Steller, 1988) and reality monitoring (Johnson & Raye, 1981) research also use the number of details in a statement as an indicator of deception (Vrij, 2019). It is possible that the location of both emotional and nonemotional details also might matter (e.g., the rate of adjectives). Our statistical classification revealed that the location of maximum affect is too limited as a tool for detection, though if it is paired with other features, detection accuracy might improve.

A careful reader might recall Ott and colleagues (2011) observed that fake hotel reviews, on average, contained fewer negative emotion terms relative to truthful hotel reviews. This unusual effect—relative to much of the deception literature (Hancock et al., 2007; Hauch et al., 2015; Markowitz & Griffin, 2020; Newman et al., 2003)—was resolved by suggesting that fake reviewers tried to write positive reviews. While we agree with this explanation, our results suggest that a possible clarification of the Ott et al. (2011) results is the location of positive and negative affect to betray deceit. Overall rates of negative affect might be inconsistent with prior empirical and meta-analytic evidence, though the location of negative affect indeed reveals false speech in a way that would be conceptually consistent with extant deception evidence (e.g., the location of maximum affect is more pronounced and earlier in lies relative to truths).

While the exact psychological mechanism is unclear for our maximum affect result, there are several possibilities informed by prior research. For example, a potential underlying mechanism could be arousal. Some evidence suggests liars are more prone to experience increased levels of arousal than truth-tellers (Turck & Miller, 1985; Waidd & Orne, 1981). Therefore, it may be possible that liars exhibit high arousal at the beginning of the message but then regress to acclimate to the lie and expectations of the receiver. Another way arousal can come into play is via “social transmission motives.” Arousal can contribute to a message’s successful social transmission (Berger, 2011). High levels of arousal can be considered a state of activation while low levels of it can be seen as deactivation or a state of relaxation (Heilman, 1997). Therefore, if liars want their speech to grab an audience’s attention, their messages to be shared, or their arguments to be acted upon, emotion might be best placed toward the beginning of a message rather than the end. This assumes a rather deliberate, thoughtful, and goal-oriented decision by a liar that might involve conscious (Buller & Burgoon, 1996) or less conscious processes (McCornack et al., 2014). The degree to which deceptive discourse production is largely deliberate or not has received substantial debate in deception research (see Levine, 2020), and therefore, this idea warrants further testing.

Limitations and Future Directions

The scope of the current investigation was limited to the location of emotion in false and truthful texts. Future research should examine how false and truthful texts differ in the relative position of other dimensions. Perhaps, maximum rates of analytic thinking are different for deceptive and honest communicators (see Markowitz, 2019; Pennebaker et al., 2014, for evaluations of analytic thinking in naturally occurring data), or the relative location of verbal abstraction (Markowitz & Hancock, 2016; see Larrimore et al., 2011). Another future area of research could test how the trend of emotions changes within text (van Laer et al., 2019).

We offer evidence of our method’s effectiveness using texts that range from 150 to 450 words on average. It is unclear how the method might apply to much longer (e.g., speeches by presidents) or shorter texts (e.g., Tweets). We therefore expect that a fruitful line of research examines the boundary conditions of the maximum affect finding, especially as many scores in our data set received the maximum value according to our coding procedure.

Another limitation is the magnitude of our effect sizes. Primary studies and meta-analytic evidence suggest deception research is rife with small- to medium-sized effects (Hauch et al., 2015; Luke, 2019), and our results support this trend. Our examinations likely benefited from scale, suggesting that future work should also seek large sample sizes to observe these effects in experimental and observational settings. Our detection accuracies using the location of maximum affect alone also are unlikely to be forensically or diagnostically effective.

Finally, we used nonspoken texts in this analysis from public and published data sets, and it is therefore unclear whether the location of maximum affect indicates deception for spoken or handwritten texts. Prior meta-analytic research suggests that the production mode of discourse (e.g., whether a text was written, typed, or spoken) is an important moderator for deception (Hauch et al., 2015), especially for emotion. Therefore, we advise future researchers to understand the degree to which the location of maximum affect is also impacted by the production mode of the discourse.

Authors’ Note

The data used in the manuscript are available in the Open Science Framework: https://osf.io/fuzp6/

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ORCID iD

Amir Sepehri https://orcid.org/0000-0002-3228-3127
David M. Markowitz https://orcid.org/0000-0002-7159-7014

Supplemental Material

The supplemental material is available in the online version of the article.

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Author Biographies

Amir Sepehri is a PhD candidate in marketing at the Ivey Business School, Western University.

David M. Markowitz is an assistant professor in the School of Journalism and Communication at the University of Oregon.

Rod Duclos is the R. A. Barford associate professor of marketing at the Ivey Business School, Western University.

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