Journal of Nonverbal Behavior (2024) 48:5–9
https://doi.org/10.1007/s10919-024-00457-w

EDITORIAL

Introduction to the Special Issue on Innovations in Nonverbal Deception Research: Promising Avenues for Advancing the Field

Sally D. Farley[1]

Accepted: 17 February 2024 / Published online: 28 February 2024

Abstract
Ekman and Friesen's (1969) seminal theoretical paper on the leakage hierarchy sparked decades of research on the relationship between nonverbal cues and deception. Yet skepticism over the strength and reliability of behavioral cues to deception has been building over the years (DePaulo et al., 2003; Patterson et al., 2023; Vrij et al., 2019). However, the last two decades have seen dramatic growth in research paradigms, interviewing techniques, integration of technology, automated coding methods, and facial research, suggesting a need for reexamination of the current state of the field. This special issue includes theoretical and empirical papers that advance our understanding of the link between nonverbal cues and deception. This collection of papers suggests there is cause for some optimism in the field of nonverbal deception detection and signals some fruitful avenues for future research. Specifically, deception research in ecologically valid, high-stakes lie-detection situations using a multi-modal approach has good promise for differentiating truth-tellers from liars.

Keywords Deception · High-stakes lies · Machine Learning · Accuracy · Nonverbal cues

Introduction

In the early morning hours of Monday March 23, 2015, Denise Huskins claimed that she and her boyfriend Aaron Quinn were awakened by a bright shining light, bound by an intruder, forced to put on duct-tape covered swim goggles, and directed by a mechanical-sounding voice to drink a sedative. The intruder then forced Huskins into the trunk of his car, took her to his South Tahoe home, and sexually assaulted her twice before releasing her two days later 400 miles away. This story, featured in the 2024 Netflix docuseries "American Night-

✉ Sally D. Farley
sfarley@ubalt.edu

1 College of Arts and Sciences, University of Baltimore, Baltimore, USA

mare," seemed wildly implausible, so it was not surprising that at first, Aaron Quinn fell under suspicion. His delay in reporting his girlfriend's abduction and his flat affect during interrogation seemed to signify guilt. But shortly thereafter, the narrative promulgated by the press was that the abduction had never taken place at all and that the couple had perpetrated a hoax. Both Quinn and Huskins were questioned extensively, but they were never able to convince police that the abduction was real. This remarkable *true* story (the offender, Matthew Muller, former Marine and Harvard-trained attorney, later confessed to the crime) highlights the complex dynamics of lie-detection in high stakes situations. As the docuseries unfolded, watchers carefully scrutinized the nonverbal behavior of the couple, looking for cues of deception, and many of us believed that at least one member of the couple was guilty. The recent attention to this story and countless other crime suspects of the past and present, pose an important and consequential question for researchers: Are there reliable nonverbal cues to deception?

The belief that deception is revealed through nonverbal behavior has a long history, but doubts about the strength of the relationship between deception and nonverbal cues has been building in recent years (Patterson et al., 2023; Vrij et al., 2019). Ekman and Friesen (1969) published the first theoretical formulation of nonverbal behavior and deception, igniting decades of empirical research. Their work was heavily inspired by Freud, who famously wrote, "If his lips are silent, he chatters with his finger-tips: betrayal oozes out of him at every pore" (Freud, 1905, p. 94 as cited in Ekman & Friesen, 1969). Ekman and Friesen's (1969) leakage hierarchy held that nonverbal cues which we are practiced at controlling, such as the face, are less revealing (leaky) about possible deception than cues to which we attend less, such as the legs and feet. Although this theory has a great deal of intuitive appeal and has been profoundly influential in popular media and television, it has come under attack in recent years in part for failing to delineate *which* emotional states liars and truth-tellers feel and *when* (Vrij et al., 2019). One particularly sticky issue for this theory is it fails to account for the fact that anxiety does not discriminate truth-tellers from liars. Truth-tellers and liars may both be anxious for different reasons; the truth-teller for fear of being incorrectly labeled a liar and the liar for being found out.

Since Ekman and Friesen's seminal (1969) paper, additional theoretical accounts for the link between nonverbal behavior and deception have been advanced, with cognitive theories offering the most promising alternative to Ekman's leakage hierarchy. Cognitive load theory (Vrij et al., 2017) recast the focus from emotion to cognition, arguing that it is more cognitively taxing to lie than it is to tell the truth. As a result, interventions aimed at increasing cognitive load (such as requiring interviewees to answer unexpected questions or telling their stories in reverse order) are presumed to magnify behavioral cues that differentiate truth-tellers and liars. A meta-analysis of 14 studies revealed that increasing the cognitive demands on interviewees increased lie detection accuracy from 47% for standard conditions to 67% conditions that imposed additional cognitive load (Vrij et al., 2017). While these results are promising, the cognitive load approach yields differences in verbal, as opposed to nonverbal, cues, and the link between nonverbal behavior and deception has been on unsure footing for many years. DePaulo et al. (2003) published a comprehensive, influential meta-analysis based on 1338 estimates of 158 cues to deception, finding that "many behaviors showed no discernible links, if only weak links, to deceit" (p. 74). In their *Annual Review of Psychology* paper, Vrij et al. (2019) reached a similar dismal conclusion, as did Patterson et al. (2023), maintaining that the evidentiary link between nonverbal behavior and deception was "faint and unreliable" (p. 312). These are fair critiques based on DePaulo's exhaustive review of the field in 2003, but more than 20 years has elapsed since this meta-analysis was published and this time period has seen dramatic growth in research paradigms, interviewing techniques, integration of technology, and automated coding methods. Given these advances, are nonverbal cues to deception as "faint and unreliable" as previously thought? The purpose of this special issue is to showcase cutting-edge empirical research on nonverbal deception detection, along with critical review articles, to shine a spotlight on the current state of the field after decades of research in this area.

The opening paper by Matsumoto and Wilson (2023) reexamined the data sourced from DePaulo et al.'s meta-analysis (2003). They argued that most of the studies incorporated into that meta-analysis suffered from poor ecological validity, specifically, solitary (not dyadic) laboratory-based lie-detection tasks with low stakes. Furthermore, the meta-analysis examined nonverbal behaviors singly, rather than as a group. Matsumoto and Wilson (2023) affirmed the conclusions of Hartwig and Bond (2014), based on their more recent meta-analysis, that "signals of deception are manifested in constellations rather than single cues" (p. 667). They concluded that research involving more realistic high stakes deception situations using a multimodal approach (including the face, which has seen substantial coding advances in the last 20 years) will likely yield significantly higher accuracy rates than those found in DePaulo et al. (2003).

The next group of papers focused attention on nonverbal cues in the face. Deeb et al. (2024) tested the intuitive assumption that increasing rapport through affiliative nonverbal behavior would increase disclosure and honesty in information gathering interviews. Although individuals told to tell the truth provided more accurate details and more total details than those told to lie, revealing that they were more forthcoming, the nodding behavior of the interviewer did not affect veracity cues. This research suggests that nodding behavior, when examined by itself, may not be an influential determinant of interviewee behavior. Colasanti et al. (2023) conducted the first investigation of eye gaze patterns of individuals viewing a complex scene as a function of guilt or innocence. "Guilty" participants who were told to lie about stealing an exam from a professor's office fixated less on the location of the room where the exam was stolen than did "innocent" participants. This paper helps to reconcile contradictory findings about gaze fixation in deception contexts, finding that guilty people gaze less (not more) at "critical" locations where "crimes" have taken place. Using a rare dyadic deception paradigm, Solbu et al. (2023) examined the role of negative facial emotion (fear, contempt, anger, disgust and sadness) in signaling deception. They compared dyads of low, moderate, and high levels of initial rapport as defined by synchrony of Duchenne smiles. For dyads with established rapport (moderate or high levels), negative emotions that deviated from verbal content differentiated truth-tellers from liars significantly more so than dyads with low rapport, showing that discrepant emotions were a predictor of deception.

Two contributions to the special issue leveraged innovative machine learning approaches to ascertain if these methods outperformed traditional approaches to lie-detection. Focusing on the accuracy of these methods is particularly important given the increase in problematic deception detection protocols used at airports, such as SPOT (Denault et al., 2020). Delmas et al. (2024) conducted a systematic review of 28 studies on the accuracy of machine learning lie detection systems that rely on facial cues. In a comprehensive description of machine learning systems, the classifiers used in these programs, the moderators of the effects, and limitations of machine learning approaches, Delmas et al. (2024) found that automatic methods using facial features distinguish between truth-tellers and liars with 62 to 73% accuracy. These accuracy estimates are comparable to the 68% accuracy rate reported by Hartwig and Bond (2014) based on constellations of cues instead of single cues. Poppe et al. (2024) shifted their focus from the face to the body, reanalyzing data from Van der Zee et al. (2019) using a machine learning approach. The machine learning system resulted in lie-detection rates between 60 and 70%, well above the 53% accuracy based on human judgments reported in Van der Zee et al. (2019). Cues that were more predictive of differentiating truth-tellers from liars were the arms (particularly the left arm), body symmetry, and upper body (as opposed to the legs and feet), but this paper also found that clusters of cues outperformed single cues.

The final paper by Zloteanu and Vuorre (2024) provides a comprehensive tutorial for conducting signal detection analyses on truth versus lie distinctions. Zloteanu and Vuorre (2024) highlighted the issues of traditional ANOVA-based models of analysis for lie-detection research such as the need for data transformation, listwise deletions for missing data, and the approach of collapsing judgments across items or judges, which may inflate accuracy estimates. The signal detection approach offers a robust alternative to traditional ANOVA-based models that captures (rather than ignores) individual differences of items and judges and can flexibly accommodate a variety of experimental designs. Future research will benefit from using the data analysis procedure that these authors so clearly described.

These papers suggest that the landscape in the nonverbal deception area is not as bleak as was previously thought and signal some fruitful avenues for future research. Few research studies incorporated into DePaulo et al.'s (2003) meta-analysis focused their attention on the face, potentially because the paper preceded Ekman's (2005) development of the FACS system. Recent decades have seen a revolution of technological advances to tackle complex and subtle nonverbal changes, and the studies in this special issue point to eye gaze (Colasanti et al., 2023), and machine learning approaches that aggregate constellations of nonverbal cues (Delmas et al., 2024; Poppe et al., 2024) as promising paths forward. Ideally, future deception researchers will undertake deception research using a multi-modal approach, in ecologically valid, high-stakes lie-detection situations that involve dyadic conversation, such as interrogation interviews (Matsumoto & Wilson, 2023). One oft-neglected channel of deception is the voice; in DePaulo et al.'s (2003) meta-analysis, vocal immediacy, vocal tension, inconsistency between channels (such as the voice and face) and vocal pitch had effect sizes ranging from 0.21 to 0.55 (when combined with verbal immediacy). Especially given recent advancements in the ability to modulate parameters of the voice with Praat (Phonetic and acoustic analysis toolkit; Boersma & Weenink, 2024), vocal deception research seems a ripe area for investigation.

A final thought about future research pertains to the unique example of lying about positive emotions. "Leaky" negative emotional states are typically viewed as evidence of deception (e.g. Solbu et al., 2023). Yet, it is not uncommon for people to hide excitement about pregnancy in its early stages (for fear of miscarriage), or disguise feelings of love (when the target is not one's romantic partner). In these cases, does masked *positive* emotion betray deception? Are individuals more successful at deceiving others in high-stakes positive situations than high-stakes negative situations? Might women's nonverbal advantage (Knapp et al., 2021) give them an edge at deciphering relational lies of this sort? Deception researchers would profit from shedding light on these interesting questions.

Author Contributions The manuscript was written by Sally Farley and edited by Leanne ten Brinke.

Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

References

Boersma, P., & Weenink, D. (2024). Praat: Doing phonetics by computer [Computer program]. Version 6.4.05, retrieved 27 January 2024 from http://www.praat.org/.

Colasanti, M., Melis, G., Monaro, M., Ricci, E., Bosco, F., Rossi, M., & Roma, P. (2023). Did you commit a crime there? Investigating the visual exploration patterns of guilty, innocent, honest, and dishonest subjects when viewing a complex mock crime scene. *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-023-00438-5.

Deeb, H., Leal, S., Vrij, A., Mann, S., & Dabrowna, O. (2024). To nod or not to nod: How does interviewer nonverbal behavior affect rapport perceptions and recall in truth tellers and lie tellers? *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-024-00452-1.

Delmas, H., Denault, V., Burgoon, J., & Dunbar, N. E. (2024). A review of automatic lie detection from facial features. *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-024-00451-2

Denault, V., Plusquellec, P., Jupe, L. M., St-Yves, M., Dunbar, N. E., Hartwig, M., & van Koppen, P. J. (2020). The analysis of nonverbal communication: The dangers of pseudoscience in security and justice contexts. *Anuario De Psicología Jurídica*, *30*, 1–12. https://doi.org/10.5093/apj2019a9.

DePaulo, B. M., Lindsay, J. J., Malone, B. E., Muhlenbruck, L., Charlton, K., & Cooper, H. (2003). Cues to deception. *Psychological Bulletin*, *129*, 74–118. https://doi.org/10.1037/0033-2909.129.1.74.

Ekman, P., & Friesen, W. V. (1969). Nonverbal leakage and clues to deception. *Psychiatry*, *32*, 88–106.

Ekman, P., & Rosenberg, E. L. (Eds.). (2005). *What the face reveals: Basic and applied studies of spontaneous expression using the facial action coding system (FACS)* (2nd ed.). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195179644.001.0001.

Hartwig, M., & Bond, C. F. Jr. (2014). Lie detection from multiple cues: A meta-analysis. *Applied Cognitive Psychology*, *28*, 661–667. https://doi.org/10.1002/acp.3052.

Knapp, M. L., Hall, J. A., & Horgan, T. G. (2021). Nonverbal communication in human interaction (9th ed.). Kendall Hunt. ISBN: 978-1-79241-066-6.

Matsumoto, D., & Wilson, M. (2023). Behavioral indicators of deception and associated mental states: Scientific myths and realities. *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-023-00441-w.

Patterson, M. L., Fridlund, A. J., & Crivelli, C. (2023). Four misconceptions about nonverbal communication. *Perspectives on Psychological Science*, *18*, 1388–1411. https://doi.org/10.1177/17456916221148142.

Poppe, R., van der Zee, S., Taylor, P. J., Anderson, R. J., & Veltkamp, R. C. (2024). Mining bodily cues to deception. *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-023-00450-9.

Solbu, A., Frank, M. G., Xu, F., Nwogu, I., & Neurohr, M. (2023). The effect of synchrony of happiness on facial expression of negative emotion when lying. *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-023-00447-4.

Van der Zee, S., Poppe, R., Taylor, P. J., & Anderson, R. J. (2019). To freeze or not to freeze: A culture-sensitive motion capture approach to detecting deceit. *Plos One*, *14*(4), e0215000. https://doi.org/10.1371/journal.pone.0215000.

Vrij, A., Fisher, R. P., & Blank, H. (2017). A cognitive approach to lie detection: A meta-analysis. *Legal and Criminological Psychology*, *22*(1), 1–21. https://doi.org/10.1111/lcrp.12088. https://doi-org.proxy-ub.researchport.umd.edu/.

Vrij, A., Hartwig, M., & Granhag, P. A. (2019). Reading lies: Nonverbal communication and deception. *Annual Review of Psychology*, *70*, 295–317.

Zloteanu, M., & Vuorre, M. (2024). A tutorial for deception detection analysis or: How I learned to stop aggregating veracity judgments and embraced signal detection theory mixed models. *Journal of Nonverbal Behavior*. https://doi.org/10.1007/s10919-024-00456-x.