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Veracity judgement, not accuracy: Reconsidering the role of facial expressions, empathy, and emotion recognition training on deception detection

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Abstract

People hold strong beliefs about the role of emotional cues in detecting deception. While research on the diagnostic value of such cues has been mixed, their influence on human veracity judgements is yet to be fully explored. Here, we address the relationship between emotional information and veracity judgements. In Study 1, the role of emotion recognition in the process of detecting naturalistic lies was investigated. Decoders' veracity judgements were compared based on differences in trait empathy and their ability to recognise microexpressions and subtle expressions. Accuracy was found to be unrelated to facial cue recognition and negatively related to empathy. In Study 2, we manipulated decoders' emotion recognition ability and the type of lies they saw: experiential or affective (emotional and unemotional). Decoders received either emotion recognition training, bogus training, or no training. In all scenarios, training did not affect veracity judgements. Experiential lies were easier to detect than affective lies; however, affective unemotional lies were overall the hardest to judge. The findings illustrate the complex relationship between emotion recognition and veracity judgements, with abilities for facial cue detection being high yet unrelated to deception accuracy.

Keywords

Emotion recognition; deception detection; lie; training; facial expression; empathy

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Introduction

Decades of deception research have consistently found that human lie detection ability is poor (Bond & DePaulo, 2006). People are also overconfident in their ability (Holm & Kawagoe, 2010) and biased towards assuming that most statements are honest (i.e., truth-biased; Levine et al., 1999). Some scholars argue that decoders' lacklustre performance is due to their inability to detect subtle behavioural differences between liars and truth-tellers, especially related to emotions (Ekman, 2003a). Implicitly, this assumes that (1) there exist diagnostic behavioural cues of deceit, and (2) decoders can make rational veracity judgements if they use such cues. This approach has resulted in a theoretical standstill (partly due to the low reliability of behavioural cues in predicting deception) and a lack of research on people's veracity judgement processes.

Indeed, there are few theoretical models of human veracity judgement, with both classical (e.g., Zuckerman,

DePaulo, & Rosenthal, 1981) and newer attempts (e.g., Levine, 2014b; Street, 2015) placing a growing emphasis on decoders' perception of alleged "cues of deceit," thereby using accuracy as the primary metric of interest. Here, we recontextualise human deception detection, moving away from a focus on accuracy (i.e., the correct perception and interpretation of behavioural cues) towards a

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veracity judgement approach in which the rationale, predictions, and interpretation of effects are conceptualised as a judgmental process. We illustrate how deception research can develop new theoretical insights by shifting focus from accuracy to veracity judgements.

Emotion-based lie detection

Arguably the most influential perspective in deception detection research has been the emotion-based approach (EBA). The EBA purports the existence of behavioural differences between liars and truth-tellers relating to the emotions senders experience (Ekman, 2003a). Liars will "leak" subtle behavioural cues that betray their lies, referred to as *emotional cues* (Ekman & Friesen, 1969). The EBA argues that a decoder's ability to recognise emotional cues relates to their ability to detect deception, with more perceptive decoders being more accurate (Ekman, 2009).

An important aspect that is often overlooked relates to potential differences between the claim of emotional cues being diagnostic of deceit and the claim that people can use such cues to make accurate veracity judgements. The EBA tends to conflate the two, with poor accuracy being attributed to the absence of such cues and/or the decoder's lack of knowledge of such cues. This assumes that humans have the perceptual and cognitive mechanisms necessary to utilise emotional cues to make rational decisions.

The first claim has received little support in the literature. While research finds that some behaviours are associated with deceit (Hartwig & Bond, 2014; Hurley & Frank, 2011), these are scarce, unreliable, and rarely veracity-specific (DePaulo et al., 2003). Indeed, Luke (2019) recently argued that past findings on deceptive cues should be treated with caution and scepticism as they can be explained by a combination of publication bias and questionable research practices. As such, being an astute decoder has little bearing on accurate veracity judgements if there are no reliable cues to decode. The second claim is the focus of the current article.

Given this lack of empirical support for reliable emotional cues, the EBA has been heavily disparaged (Burgoon, 2018; Vrij, 2008). In this article, we argue that emotions should not be overlooked in deception research as they are important for understanding human veracity judgements. Such research is relevant given the rise in emotion-based deception detection programmes being proposed or implemented in real-world scenarios, seemingly disregarding the criticisms levied against them (Burgoon, 2018; Denault et al., 2020; Zloteanu, 2020). Shifting focus from accuracy to veracity judgements can provide new insights regarding emotions and deception. In line with this proposition, the present research explores how decoders' emotion recognition ability and senders' emotions influence veracity judgements.

Emotional cues

Emotional cues are argued to result from the emotions associated with lying (e.g., fear or guilt), thereby producing uncontrollable behaviours that betray the lie (i.e., the *leakage hypothesis*; Ekman & Friesen, 1969). EBA proponents argue that facial expressions are the strongest source of such cues (Ekman, 2003b). The reasoning for this is twofold. First, genuine facial expressions of emotion are involuntary and insuppressible (Hurley & Frank, 2011), meaning that they always occur when lying. Second, genuine and deceptive emotional expressions differ in their appearance as the facial muscles involved in real affect cannot be voluntarily activated, called *reliable muscles* (Ekman, 2003b). Below, we consider each point.

The few studies to investigate the leakage hypothesis relied on video analysis for the presence of emotional cues. Such research reported that, in both laboratory (Frank & Ekman, 1997) and naturalistic conditions (Porter et al., 2012; Porter & ten Brinke, 2008), lies and truths could be classified to a degree based on emotional cues. However, even when using a frame-by-frame analysis, the number of cues was minuscule and no emotion was found to be veracity-specific (Porter et al., 2012), contradicting the core tenant of this approach. Of note, such results do not reflect the overall trend in the literature. Meta-analyses find that emotional cues are not reliable predictors of deception (DePaulo et al., 2003) nor does the emotionality of the lie predict its detectability (Hartwig & Bond, 2014).

The foundation of the "reliable muscles" perspective stems from early research on smiling, proposing clear differences between genuine and nongenuine smiles (first noted by Duchenne, 1862; Ekman, 2003b). However, robust examinations have found little evidence for muscles to activate only during genuine displays or genuine displays sharing a unique appearance (Krumhuber & Manstead, 2009). This is unsurprising as emotion scholars contend that internal emotional states and external expressions are related but separate phenomena (Gunnery & Hall, 2014). Thus, there is little reason to assume a priori that emotional cues would be diagnostic of deceit.

So far, investigations of the diagnostic relation between emotional cues and deception lack empirical and theoretical support. Even those studies which report the presence of emotional cues for achieving classification accuracy (through video coding) fail to obtain consistent results, partly because human decoders cannot reliably detect veracity above chance performance (Frank & Ekman, 1997; Porter et al., 2012). Thus, even if emotional cues exist, without the use of technology people do not or cannot use such information to improve accuracy.

Nonetheless, it would be erroneous to conclude that emotions do not play a role in the veracity judgement process. Regardless of their diagnostic value, emotional

cues—especially facial expressions—affect naïve observers' judgements (Stewart et al., 2009). Facial expressions receive preferential attention (Fernández-Dols et al., 1991) and processing in the brain (Vuilleumier et al., 2001). People make quick inferences of others based on their facial expressions, even when briefly presented (Willis & Todorov, 2006), and can reliably classify facial expression of emotions with high accuracy (Ekman, 2003b; Nelson & Russell, 2013). However, they are not accurate at determining whether the emotions they perceive are genuine or fabricated (Krumhuber et al., 2014; Zloteanu et al., 2018, in press).

Cross-culturally, people hold strong beliefs that facial expressions and emotion-related behaviour can predict deception, which in turn often heavily influences their assessment of veracity (Bogaard et al., 2016; The Global Deception Research Team, 2006). Given that people prefer, focus on, and assign more weight to nonverbal information when making judgements about others (see Bond et al., 2013), a picture emerges where emotional cues are less a tool for detecting deception and more a source for bias and inaccuracy.

Veracity judgements

The literature on veracity judgements is complex and spans beyond emotion-based research. Within that realm, the truth-bias is one of the most reliable effects (Bond & DePaulo, 2006; Hartwig & Bond, 2014), describing a phenomenon where people tend to assume that most information is honest unless prompted otherwise (also referred to as "truth default"; Gilbert et al., 1988, 1990). In the deception literature, the truth-bias can be regarded as an overestimation of the proportion of truths and an underestimation of the proportion lies within a sample (McCornack & Parks, 1986; Zuckerman, DePaulo, & Rosenthal, 1981).

Recent accounts propose that "bias" may not be the correct interpretation of such a phenomenon. The Truth Default Theory (TDT; Levine, 2014b) proposes that telling the truth is the default state for humans. As such, to accurately detect deception, decoders must overcome this default. Conversely, the Adaptive Lie Detector (ALIED; Street, 2015) account argues that the truth-bias is an experience-based heuristic. ALIED argues that people's position is based on context. In situations where lying is infrequent, people will assume that others are honest most of the time. In situations where lying may be frequent (e.g., police interviews), people will assume more dishonesty. This also explains the shift in truth-bias and the existence of a lie-bias (i.e., an overestimation of lies) in situations of suspiciousness (Kim & Levine, 2011; Masip et al., 2009; McCornack & Levine, 1990; Meissner & Kassin, 2002). Both approaches still emphasise that people decode and make judgements based on behavioural cues.

Another often overlooked veracity effect is the demeanour bias (Levine, 2010; Riggio & Friedman, 1983). It describes the phenomenon of some senders producing a general impression of honesty (or dishonesty) regardless of their veracity (Riggio et al., 1987; Zuckerman, Larrance, et al., 1981). This has been proposed as an explanation for the slightly (but consistently) above chance deception detection performance of decoders (i.e., the existence of a few "transparent" liars; Levine, 2016) and for the variability in detection scores across studies. Thus, some judgement patterns may be better accounted for by differences between senders than by decoder ability.

Adding further complexity, one must consider that deception is a dynamic process requiring a sender and a decoder. According to Interpersonal Deception Theory (IDT; Buller & Burgoon, 1996), this interactivity is fundamental to the deception process. In IDT, the bidirectional nature of the sender–decoder interaction can influence not only the behaviour of the liar but also that of the decoder (Burgoon et al., 1999). Thus, deception and its detection are complex and multifaceted (for a recent overview, see Sternglanz et al., 2019). Our current exploration is focused on the emotion-based dimension of this larger problem.

Present research

This research explores the role of emotion recognition and emotional cues in decoder veracity judgements. Typical investigations of human deception detection assume that detectable cues exist, thereby focusing on differences and manipulations which may relate to their perception or efficient usage. This is not the approach taken here, and in fact, it is one we criticise. We propose that emotional cues do not reliably relate to deception detection, yet such "cues" do affect people's judgement. We argue for a shift from *deception detection accuracy* to *veracity judgement* with a focus on the decoder's judgement process. Typically, decoders are treated as if performing an *intellective task* (such as an arithmetic problem, where a correct answer exists and problem solving relates to ability and information). We think it is more appropriate to consider decoders as performing a *judgmental task* (such as jury verdicts, where a "correct" answer is a contentious point and investigations explore how judgements form; see Carey & Laughlin, 2011). The present research investigates the effect of emotional information on decoders' judgements, varying either as a function of individual differences (Study 1) or experimental manipulation (Study 2).

For this purpose, several assumptions of the EBA were addressed. First, more perceptive decoders are better at detecting deception. Second, training in emotional cues can aid deception detection. Third, accuracy for detecting deception is higher if the lies contain an emotional element. We strongly argue that emotions should not be disregarded in deception research. While the literature suggests

that emotional cues (such as facial expressions) are not diagnostic of deception (especially for human decoders), the current work aims to show that emotional information can affect how people judge others. By focusing on the role emotions have on veracity judgements, we shall gain novel insights into human deception detection.

Study 1

The first study explored the primary assumption of the EBA regarding the relationship between human lie detection ability (i.e., real-time detection, unaided by technology) and emotion recognition (i.e., perceiving and interpreting emotional information from others' behaviour). To that end, two components of the emotion recognition construct were considered: facial expression classification and empathy.

Facial expressions of emotions

In the following, two types of facial expressions were examined that have been proposed by the EBA as relevant to detecting deception: microexpressions and subtle expressions.

Microexpressions are full-faced expressions occurring at <0.5 of a second, resulting from failed attempts to mask or suppress one's true emotions (Ekman, 2003a; Frank & Svetieva, 2015), and have been linked to deception detection (Ekman & Friesen, 1969; Porter & ten Brinke, 2008). However, the use of microexpressions as cues to detect deception is controversial due to the lack of empirical support for this relationship (see Burgoon, 2018; Zloteanu, 2020).

Subtle expressions are partial expressions of suppressed or masked affect, displayed with only fragments of the prototypical expression musculature. Unlike microexpressions, their presentation is longer in duration, but they are also more ambiguous (Ekman, 2003a; Matsumoto & Hwang, 2011). While few studies have researched subtle expressions, EBA proponents have suggested that their recognition does relate to veracity judgements (e.g., Matsumoto et al., 2014; Warren et al., 2009).

Empathy

The second component is empathy, i.e., the ability to accurately perceive and interpret others' emotions (Singer, 2006). Empathy is considered necessary for social communication, predicting behaviour, and the identification of emotions (Keysers, 2013). Empathy relates to the accurate recognition of facial expressions (Besel & Yuille, 2010), even subliminally presented (Prochnow et al., 2013), and can aid the detection of mismatched emotions (Wojciechowski et al., 2014)—all aspects which form part of the EBA.

Research on the relationship between empathy and deception detection is scarce. Being more empathic relates to better emotional cue classification (Svetieva & Frank, 2016) but also poorer veracity judgements (Baker et al., 2013; Israel et al., 2014). While this seems at odds with the EBA's claims, it can be understood if one conceptualises empathy as being related to emotion classification and not affective authenticity discrimination. For instance, DesJardins and Hodges (2015)[1] found that more empathic decoders were more accurate at inferring the thoughts of their conversation partners, but only when they were being honest. Empathy may therefore be useful for inferring others' affective states *only* when the emotional cues displayed are genuine.

Facial cues and empathy are two sources EBA proponents suggest as relevant for accurate deception detection, such that being more emotionally perceptive should result in subtle emotional cues being more readily attended to and perceived by decoders. However, given the questionable reliability and diagnosticity of such cues and the poor ability of decoders to discriminate genuine from nongenuine cues, we made predictions opposite to those of the EBA, namely, that emotion recognition hinders lie detection performance.

Being able to recognise others' emotions is only useful in predicting affect if the emotional cues to be decoded are genuine, not deceptive. In deceptive scenarios, emotional cues may be more a source of uncertainty, adding decision difficulty. Hence, more emotionally perceptive decoders relying on such cues may be particularly likely to misinterpret the sender's true affective state if the cues produced are deceptive, leading to poorer deception detection performance (see also Zloteanu, 2015, 2020).

Method

Participants. Based on estimates from past research on the relationship between individual differences in emotion recognition and veracity judgements (Warren et al., 2009) and considerations for the smallest effect size of interest (SESOI), we conducted a priori power analysis (G*Power 3.1; Faul et al., 2007) to determine the sample size necessary to achieve 80% power of detecting a moderate (ρ = .4) size correlation at the traditional .05 criterion of statistical significance (one-tailed). In total, 41 participants (26 females, M_{age} = 23.7, SD = 9.7) were recruited using the university's online subject pool. Participants received course credit or £1 for their time. Informed consent was obtained from all participants, and all aspects of the experiment were approved by the university's ethics committee (CPB/2013/009).

Stimuli and materials

Empathy. Individual differences in empathy were measured using the Interpersonal Reactivity Index (IRI; Davis, 1983). This multidimensional measure consists of 28 questions, 7 specific to each of the four subscales (Per-

spective-Taking, Fantasy, Empathic Concern, and Personal Distress) to which individuals respond using a letter from A (*does not describe me well*) to E (*describes me very well*). The IRI has high internal and external validity (Davis & Franzoi, 1991) and good test–retest reliability (Davis, 1983). Presently, due to the high positive correlation between the subscales of the IRI, rs ≥ .60, ps < .001, JZS BF_{+0} > 100 (Jeffrey-Zellner-Siow Bayes factor; BF+0 refers to a one-sided (positive) BF.), the overall score for each participant was used (see Karniol & Shomroni, 1999).

Facial expression recognition. The Micro Expression Training Tool (METT; Ekman, 2002) is a self-directed training programme developed to train microexpression recognition for seven basic emotions: happiness, anger, sadness, disgust, fear, surprise, and contempt. The software offers a Pre- and Post-test, Training videos, and Practice module. The software's Pre-test module was used for Study 1. This consists of 14 colour portrait photographs of facial expressions of emotions (Japanese and Caucasians; 360×360 pixels), two for each emotion. The expressions are presented for 100 ms in-between two neutral expressions (start and finish) of the same person. The facial expressions reflect prototypical expressions of the target emotion based on facial activation patterns theorised to reflect the particular emotion (Ekman et al., 2002). The neutral expression remains on-screen until the participant selects one of the seven emotion labels visible during the test. Once all 14 faces have been classified, the participant receives a score reflecting the correct number of faces being classified. The maximum score is 100%. The METT has been used in past studies (e.g., Frank & Ekman, 1997; Warren et al., 2009) and is based on the Brief Affect Recognition Test, which has good validity and reliability (Matsumoto et al., 2000).

The Subtle Expression Training Tool (SETT; Ekman, 2002) is intended to train the recognition of subtle expressions. The software offers an Introduction, Get Acquainted, and Practice module. The Practice module was used which offers a test of subtle expression recognition, providing a percentage score at the end. The task contains 37 expressions belonging to seven basic emotions. All expressions are presented in black and white using the same Caucasian female (360×360 pixels). The target facial expression appears briefly on-screen and depicts an image morphed with the neutral expression (i.e., the facial musculature associated with each expression change). The speed of presentation of the expressions is set at the start from 1 (*slowest*) to 6 (*fastest*); the setting of 3 was used. In all trials, participants see a neutral expression until an emotion label is selected, and they control the progression to the next trial using a "Next" button. The instructions for the Practice session remain visible on-screen throughout the task.

Videos. Twenty videos (10 lies, 10 truths) were selected from the Bloomsbury Deception Set (BDS; Street et al.,

2011). Senders in the videos are describing past vacations in different countries, where half of the senders are lying (i.e., fabricating a holiday in a country they have never visited). The videos contain naturalistic lies, as the senders were not given any incentive to deceive other than being asked to help with a travel documentary and believing the film director was oblivious to any deception occurring. The videos were gender-matched for each veracity and presented in a fixed order. All videos are approximately 33 s in duration.

Design and procedure. A within-subjects correlational design was employed. Participants were measured on their ability to judge truths and lies, their confidence for each veracity decision, trait empathy, subtle, and microexpression recognition. Participants watched each video and made a veracity decision (forced choice: lie or truth), and provided their confidence on a 5-point scale ranging from "not at all confident" to "very confident." Participants then completed the SETT and METT tasks (counterbalanced). The SETT provides ongoing feedback (a "right" or "wrong" warning after classifying each expression) and offers a "try again" feature if one responds incorrectly. Participants were told to ignore this option and progress to the next expression (i.e., they were not allowed to amend their decision even if their initial classification was incorrect). Participants' initial choice was taken for calculating the accuracy score. Finally, they completed the IRI and were debriefed.

Results

The data were initially screened. One data point was excluded from all subsequent analyses using Cook's distance with a cut-off criterion of 0.5. The final sample was $N = 41$ (26 females). All data were analysed using both frequentist and Bayesian methods.

Deception detection accuracy. Overall performance on the deception detection task was 55% ($SD = 2.10$), which significantly differed from chance accuracy (50%), $t(40) = 3.04$, $p = .004$, 95% confidence interval (CI) = [0.33, 1.62], $d = 0.48$, JZS $BF_{10} = 8.61$. Considering each veracity, truth accuracy was 62% ($SD = 1.46$) and significantly above chance, $t(40) = 5.36$, $p < .001$, 95% CI = [0.76, 1.68], $d = 0.84$, JZS $BF_{10} = 4,913.52$, while lie accuracy was 48% ($SD = 1.42$) and was not different from chance, $t(40) = 1.09$, $p = .281$, 95% CI = [−0.70, 0.21], JZS $BF_{10} = 0.29$; the performance differences between veracities were significant, $t(40) = 4.63$, $p < .001$, 95% CI = [0.82, 2.10], $d = 0.72$, JZS $BF_{10} = 574.20$. A Pearson's correlation between accuracy and judgement confidence did not find a significant relationship, $r(41) = −.125$, $p = .440$, 95% CI = [−0.42, 0.19], JZS $BF_{10} = 0.26$.

Judgement bias. Participants' response bias was considered. This reflects the total number of "truth" and "lie"

judgements for the videos compared with the expected value given the base rate. Each "truth" response was coded as +1, while each "lie" response was coded as −1, then summed across the videos. A positive score indicates a truth-bias, a score of 0 indicates no bias, while a negative score indicates a lie-bias. The analysis revealed that decoders were overall truth-biased in their judgements (one-sample *t*-test), $t(40) = 4.63$, $p < .001$, 95% CI = [1.65, 4.21], $d = 0.72$, JZS $BF_{10} = 574.20$.

Facial cue recognition. Participants were able to recognise microexpressions with 65.46% ($SD = 14.30\%$) accuracy and subtle expressions with 61.25% ($SD = 10.30\%$) accuracy. To assess whether veracity judgements were related to the ability to detect facial cues, METT and SETT[2] scores were analysed using Pearson's correlations against total accuracy on the deception detection task, and subsequently with the truth and lie accuracies.

For the METT, neither overall accuracy, $r(41) = .002$, $p = .99$, 95% CI = [−0.31, 0.31], JZS $BF_{10} = 0.20$, nor truth, $r(41) = .072$, $p = .660$, 95% CI = [−0.24, 0.37], JZS $BF_{10} = 0.21$, or lie accuracy, $r(41) = −.070$, $p = .660$, 95% CI = [−0.37, 0.24], JZS $BF_{10} = 0.21$, were significantly correlated. Similarly, no significant correlations were found for the SETT scores and accuracy; either for overall, $r(40) = −.214$, $p = .190$, 95% CI = [−0.49, 0.11], JZS $BF_{10} = 0.46$; truth, $r(40) = −.194$, $p = .230$, 95% CI = [−0.48, 0.13], JZS $BF_{10} = 0.40$; or lie accuracy, $r(40) = −.108$, $p = .51$, 95% CI = [−0.42, 0.21], JZS $BF_{10} = 0.24$. SETT and METT scores also did not correlate, $r(40) = .102$, $p = .530$, 95% CI = [−0.22, 0.40], JZS $BF_{10} = 0.24$.

Empathy. Accuracy and empathy scores were significantly negatively correlated, $r(41) = −.382$, $p = .014$, 95% CI = [−0.62, −0.08], JZS $BF_{10} = 3.40$. Planned correlations for each veracity score with empathy revealed the predicted negative correlation between lie detection accuracy and empathy, $r(41) = −.362$, $p = .010$ (one-tailed), 95% CI = [−0.60, −0.06], JZS $BF_{-0} = 5.60$, but no positive correlation between truth detection accuracy and empathy, $r(41) = −.183$, $p = .130$ (one-tailed), 95% CI = [−0.47, 0.13], JZS $BF_{+0} = 0.09$.

The potential relationship between empathy and bias was also investigated but was found to be nonsignificant, $r(41) = .123$, $p = .440$, 95% CI = [−0.19, 0.42], JZS $BF_{10} = 0.26$. Similarly, the relationship between empathy and confidence was not significant, $r(41) = .065$, $p = .690$, 95% CI = [−0.25, 0.37], JZS $BF_{10} = 0.21$. Finally, empathy did not correlate with either microexpression recognition, $r(41) = .237$, $p = .136$, 95% CI = [−0.08, 0.51], JZS $BF_{10} = 0.57$, or subtle expression recognition, $r(40) = .094$, $p = .566$, 95% CI = [−0.23, 0.39], JZS $BF_{10} = 0.23$.

Empathy was also considered as a potential mediator of the facial cue recognition and judgement accuracy relationship. However, a mediation analysis did not provide any further insights, as neither the direct, $b = .015$, $t(40) =$ 0.63, $p = .532$, JZS $BF_{10} = 0.30$, nor indirect effect, $b = .001$, $t(40) = 0.011$, $p = .991$, JZS $BF_{10} = 0.20$, were statistically significant.

Discussion

The study revealed the predicted negative relationship between empathy and people's ability to detect deceptive statements. No relationship between facial cue detection and accuracy was found, although decoders were able to classify microexpressions and subtle expressions with high probability (~63%; higher than chance at 14.3%). The accuracy findings are in line with those reported in the deception field (Bond & DePaulo, 2006) and highlight the theoretical advantage of adopting a veracity judgement perspective with the use of Bayesian analyses to provide evidence for or against particular data structures.

The negative relationship between empathy and lie detection implies that being more attuned to the emotions of others may be detrimental for discerning veracity. Interestingly, empathy was not related to a systematic response tendency (i.e., bias). As such, the finding cannot be explained by empathic decoders being more inclined to believe deceptive statements (i.e., gullibility). Rather it seems likely that high empathics misinterpreted deceptive emotional cues as reflecting genuine affect, affecting their decision making, and leading to more erroneous lie judgements (see Stel & Vonk, 2009).

Empathy is a multidimensional construct and can have different effects based on context. For instance, Hubbard (2001) considered empathy as three pathways encompassing emotional empathy, cognitive empathy, and emotional contagion. In conflict-related interactions (which can involve lying scenarios), these components can operate in opposition. To that end, Duran et al. (2018) found that high empathy was related to poorer deception detection (particularly in women). This effect was argued to be due to low empathics being less affected by emotional contagion, focusing more on nonemotional cues to detect deception. Their findings resonate with those of the present research in the sense that higher empathy hinders lie detection, as decoders are misled or distracted by emotional cues which are nondiagnostic of deception. Stel and Vonk (2009) provide further supportive evidence for this claim, showing that empathy relates to emotional contagion only if the sender's emotions are perceived to be genuine.

Consequently, emotion recognition is not found to relate in positive ways to deception detection (as argued by EBA proponents) but resulted in the predicted opposite direction. Under the premise of accuracy-focused approaches, this finding would be difficult to interpret, yet by employing a veracity judgement perspective the findings are plausible: emotional information has a different effect depending on whether the scenario is deceptive or genuine. In genuine scenarios, empathy may foster successful interaction as it aids decoders in answering what

emotion the sender is trying to convey. However, being empathic can be detrimental in deceptive scenarios as the desire to engage in successful interactions may supersede the judgement of emotional authenticity. Here, empathy may not aid decoders in answering whether the sender's displayed emotion matches his or her underlying affect.

Study 2

The findings of the first study challenge the EBA which posits that more emotionally perceptive decoders are better at detecting deception. Yet, the failure to find an association between emotion recognition ability and veracity judgement does not necessarily eliminate the possibility of such a relationship under different circumstances. Proponents of the EBA, for example argue that untrained decoders typically rely on incorrect cues and require training to improve their accuracy. To expand upon the above findings, we investigated two additional EBA assumptions: (1) accuracy depends on the type of lie being decoded, and (2) training in facial cue recognition aids deception judgements. The second study also permits the examination of decoder judgement across multiple lie scenarios.

Emotion recognition training

The allure of the EBA is the supposed universality of emotional cues (Ekman, 2003a; cf. Barrett, 2011). If emotional cues generalise to all deceptive situations, training decoders to detect them should improve their overall lie-catching ability (Ekman, 2009). This assertion has been bolstered by findings showing that micro- and subtle expression identification can improve with training (Ekman & Friesen, 1974; Hurley, 2012; Matsumoto & Hwang, 2011). Furthermore, deception training providing information about how to classify emotions shows positive effects on accuracy (Ekman et al., 1991; Frank & Ekman, 1997; Shaw et al., 2013). However, such results are rare and do not seem to apply to all types of deception (Matsumoto et al., 2014).

While the effects of training on accuracy are still debated (Driskell, 2012; Hauch et al., 2014; Kassin & Fong, 1999), there is evidence for unwanted side effects from respective interventions. For example, increasing confidence in one's veracity judgements as a function of training (DePaulo & Pfeifer, 1986; Holm & Kawagoe, 2010) can have severe real-world consequences (see Weinberger, 2010). Similarly, training may alter the response tendencies of decoders towards overestimating the frequency of lies (i.e., lie-bias; Masip et al., 2009). It has also been argued that training effects may simply occur due to attentional changes brought about by the nature of the task, having little to do with accurately applying specific knowledge (DePaulo et al., 1982; Levine et al., 2005).

To systematically test the effects of training, researchers should include a bogus training (BT) condition as a control. Adding a "no training" (NT) control is in itself insufficient as it ignores any psychological effects from merely engaging in training. This is especially pertinent in the exploration of veracity judgement effects (e.g., changes in bias or confidence), yet few have considered this aspect (e.g., Jordan et al., 2019; Levine et al., 2005).

Based on the existing literature suggesting that training effects are small-to-moderate (Driskell, 2012; Hauch et al., 2014) and do not translate for emotion-specific training into improved accuracy (Jordan et al., 2019; Matsumoto et al., 2014; see also Burgoon, 2018), it seems plausible to focus on veracity judgement effects resulting from training rather than performance differences alone.

Understanding the effects of emotion recognition training (ERT) on judgement informs theoretical understanding and has real-world applications, given the emphasis previously placed on its usefulness (see Inbau et al., 2011; Owayjan et al., 2012). For example, the Transportation Security Administration in the United States has made substantial financial contributions to developing and utilising the Screening of Passengers by Observation Techniques (SPOT) approach, which relies heavily on nonverbal behavioural detection training, including microexpressions (Weinberger, 2010). Yet, multiple government accountability reports have published alarming reports of its usefulness, arguing for the absence of evidence to support this approach (see Denault et al., 2020).

Lie-type

Several moderating factors have been proposed to influence sender performance and decoder accuracy. According to the EBA, detection performance is influenced by the type of lie being decoded, the motivation of the liar (or truth-teller), and the stakes surrounding the lie. For instance, high-stakes lies (i.e., lies in which potential rewards to the liar for escaping detection or punishments for being caught are severe) are argued to be easier to detect than low-stakes lies due to the intense emotions experienced by the liar (Frank & Ekman, 1997), thereby hampering control over nonverbal behaviour (DePaulo & Kirkendol, 1989).

Under this view, added stakes should produce more frequent and pronounced emotional differences between liars and truth-tellers. Equally, the liar's motivation is argued to affect behaviour and detectability (see motivational impairment effect; DePaulo & Kirkendol, 1989). Such reasoning does have intuitive appeal, with decoders' accuracy being subject to influence by the amount and type of cues in some studies (although these may not be specifically emotional cues; Granhag & Strömwall, 2001). Furthermore, emotion recognition seems to be stable across the decoding of nonverbal cues (Schlegel et al., 2017), and more accurate decoders self-report that they rely on facial expressions for their judgements (Warren et al., 2009).

While proponents of the EBA argue that stakes/motivation increase the presence of cues and their detectability (Frank & Ekman, 1997; O'Sullivan et al., 2009), other scholars question whether these factors have comparable effects on both liars and truth-tellers, negating any diagnostic benefit (see overshadowing effect; Hartwig & Bond, 2014). Accordingly, meta-analyses find no reliable effects of either stakes, motivation, or the emotional content of the lie on detectability (Driskell, 2012; Hartwig & Bond, 2014; Hauch et al., 2014). Adding further complexity, the stability of human lie detection performance across scenarios remains to be debated, with some researchers finding stable decoder performances (Frank & Ekman, 1997) while others do not (Vrij et al., 2006).

Taking into account the EBA's assumptions, the equivocal research, and our focus on veracity judgements, we employed multiple video sets containing different types of lies. The first set contained naturalistic, unmotivated lies told by individuals assisting with a travel documentary (see Study 1). These represent experiential lies that one may encounter in daily life, where the sender is telling a story relating to an event that may or may not have occurred. The second set contained lies related to an emotionally charged event the sender is experiencing, where they are either retelling or fabricating their affective experience (see "Stimuli and materials" section; Warren et al., 2009). These videos can be divided into two subsets: emotional or unemotional. If the sender was lying about experiencing an affective event when in reality their experience was neutral, it is referred to as an unemotional lie (i.e., they are fabricating an emotion). If the sender was lying about experiencing a neutral event when they were experiencing an affective event, it is referred to as an emotional lie (i.e., they are suppressing an emotion).

Utilising multiple lie scenarios allows for an exploration of decoders' veracity judgement change as a function of the lie-type, as well as the stability of their capacity for detection across scenarios. Specifically, decoders who rely more on emotional cues for their performance may be better/worse overall or they may demonstrate lie-type-specific differences.

We manipulated decoders' ability to recognise emotional cues by providing ERT which we compared with BT or NT. It was hypothesised that (1) receiving ERT (real or bogus) would result in differences in veracity judgements and confidence as compared with receiving NT and (2) decoders' veracity judgements would differ based on the type of lie decoded.

Method

Participants. In total, 106 participants (84 females; M_{age} = 20.9, SD = 4.7) were recruited through the university's online subject pool. A priori power analysis for an interaction between training condition (3), veracity (2), and lie-type (2), assuming a medium-sized effect (Cohen's f =

0.18), determined that this sample size would be sufficient for 80% power. Participants received course credits for participating. Informed consent was obtained from all participants. Ethical approval was granted by the university's ethics committee.

Stimuli and materials

Videos. Twenty videos (10 lies) were selected from the BDS. The lies told by senders refer to an experiential episode (a past real or fabricated vacation). As the senders were given no incentive to lie, it can be assumed that the stakes and motivations to lie were low. The videos were controlled for gender in each veracity and were presented in a fixed order.

The 20 videos (10 lies) from Warren et al. (2009) were used. Senders watched a Hawaiian landscape footage or a surgical procedure (in counterbalanced order), used to induce mildly positive or severely negative affective responses, respectively. Senders were asked to lie by describing the video they saw as if it was the opposite video. Thus, if they saw the Hawaiian footage they would describe it as if watching the surgical video, and vice-versa. For their second recording, the senders watched the remaining video and described it truthfully. The senders also initially recorded a brief (30 s) description of their hobbies or interests serving as a baseline of their behaviour. The two subsets of the affective videos were also considered: an emotional set (five lies, five truths) in which the sender watched the surgical videos and an unemotional set (five lies, five truths) in which the sender watched the pleasant beach scene. All senders were told that "their performance would be judged," and if successful in their deception, they "would win £10" (Warren et al., 2009, p. 62), adding additional motivation and incentive for senders to be believed. The final videos are approximately 1 min in length, each containing a baseline and either a deceptive or truthful statement. The selected videos were controlled to not display the same sender twice.

ERT. The training programme was constructed using the Training and Practice modules of the METT and the SETT.

The METT's training module contains four instructional videos describing the seven basic facial expressions: anger vs. disgust, contempt vs. happy, fear vs. surprise, fear vs. sadness. The videos provide distinctions between the respective expressions and explain their correct interpretation. The Practice module contains 28 microexpressions, presented at 100 ms, to which users respond by selecting one of the seven emotion labels visible on-screen throughout the task. If they make an incorrect choice, they can choose to reveal the expression and its correct emotion. The user decides at which rate he or she wishes to progress through the trials with the use of a "Next" button. The Post-test module used in this study contains 14 facial expressions for classification; these are different from

those of the Pre-test. An accuracy score is provided (out of 100%) at the end.

The SETT's Get Acquainted training module illustrates multiple subtle expressions for the seven emotions and provides written explanations for their meaning and correct interpretation. The user decides the progression rate through each emotion, by clicking a "Next" button whenever they are ready to see a new expression. The Practice module offers a recognition test with 37 expressions presented at a predetermined speed; the slowest speed was used to give participants time to fully understand the expressions. Unlike in Study 1, participants could use a "Try again" function when they classified an expression incorrectly as the aim of the SETT here was training. This gave them the chance to select another emotion label after witnessing the subtle expression again. At the top right side of the screen, a performance colour-coded score from 1 to 5 was visible which updated based on their performance. Participants were also given instant feedback on their decisions in the form of either the word "Wrong" (and a red dot) or "Right" (and a green dot) appearing after the selection is made. A score is displayed (out of 100%) at the end.

Design and procedure. A three-way mixed design was employed. The between-subject variable was Training (ERT, BT, and NT), and the within-subjects variables were Veracity (lie and truth) and Lie-type (experiential and affective). The dependent variables were accuracy, confidence, and response bias. Participants were randomly assigned to one of the three conditions: ERT ($n = 39$), BT ($n = 38$), and NT ($n = 29$).

In the ERT condition, participants undertook the ERT. For this, they could progress through each component at their own pace. The two video rating tasks were then presented in a counterbalanced order. For each video, they had to state their decision (forced choice: lie or truth) and confidence using a 5-point Likert-type scale. The procedure took around 65 min.

In the BT condition, participants engaged in a fake training programme containing no cues of deception or emotion. The programme was created using the neutral expressions from the METT practice module. Participants were told that the task trains them to "spot subtle differences in the face, which translate to spotting cues of deception." They were shown a fixation cross, followed by a face that remained on screen for a predetermined period and was replaced with a fixation cross followed by a multiple-choice question. There were three blocks with different presentation times: slow (1 s), medium (0.75 s), and fast (0.5 s). Each block contained 18 faces that were controlled for gender. The questions targeted the age, eye colour, hair colour, and facial features of the person in the photo. For each question, participants were given four possible responses, e.g., "What was the person's eye colour?" with answers "A. Blue, B. Green, C. Brown, D. Black."

The BT was created in MATLAB (R2012b, v8.0). Afterwards, participants were given the video rating tasks. The procedure took around 45 min.

In the NT condition, participants immediately completed the video rating tasks in which they provided veracity and confidence responses. The procedure lasted around 35 min.

Participants in the ERT and BT conditions were also asked about the perceived effectiveness of the training: "How effective was the training program?" with response options from 1 (*not at all effective*) to 5 (*extremely effective*).

Results

All analyses (frequentist and Bayesian) account for truth and lie scores separately, as recommended for training investigations (see Hauch et al., 2014; Levine et al., 1999).

Deception detection accuracy. Participant veracity responses were analysed to form two variables: accuracy and response bias. Accuracy was calculated by matching the veracity of the videos with the response participants gave (coded as "correct" or "incorrect"). This was then summed for each veracity and lie-type forming a percentage score. To assess response bias, the veracity responses of participants were calculated as described in Study 1.

Overall accuracy was 55.35% for the Experiential videos and 44.6% for the Affective videos. To consider how the type of lie affected participants' veracity judgements, an analysis considering training and lie-type was conducted on veracity. A manipulation check revealed no difference in perceived training effectiveness between the ERT and BT conditions, $t(75) = -0.241$, $p = .81$, 95% CI $= [-0.31, 0.24]$, JZS $BF_{10} = 0.24$.

The results revealed a main effect of lie-type, $F(1, 103) = 41.41$, $p < .001$, $\eta_p^2 = .287$, 90% CI $= [0.17, 0.39]$, JZS $BF_{10} = 5.8e^8$, with higher accuracy for Experiential videos ($M = 55.33\%$, $SD = 12.48\%$) than Affective videos ($M = 44.58\%$, $SD = 10.12\%$), and a main effect of Veracity, $F(1, 103) = 66.73$, $p < .001$, $\eta_p^2 = .393$, 90% CI $= [0.27, 0.50]$, JZS $BF_{10} = 1.3e^{11}$, as overall truths ($M = 55.94\%$, $SD = 15.23\%$) were easier to detect than lies ($M = 44.62\%$, $SD = 15.59\%$). There was no effect of Training on accuracy, $F(2, 103) = 1.05$, $p = .354$, JZS $BF_{10} = 0.10$. The interaction between Lie-type and Veracity was found to be significant, $F(1, 103) = 16.37$, $p < .001$, $\eta_p^2 = .137$, 90% CI $= [0.05, 0.24]$, JZS $BF_{10} = 305.17$; no other interaction term was statistically significant, $Fs < .929$, $ps > .398$, JZS $BF_{10} < 0.12$.

The Lie-type by Veracity interaction was unpacked—first considering differences based on Lie-type. Simple effects revealed a significant difference in truth judgements, $F(1, 103) = 59.64$, $p < .001$, $\eta_p^2 = .367$, 90% CI $= [0.25, 0.47]$, JZS $BF_{10} = 1.2e^{11}$, with higher accuracy for Experiential videos ($M = 63.9\%$, $SD = 16.8\%$) compared
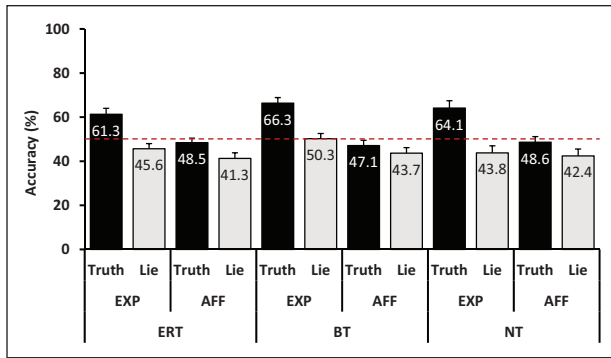
Figure 1. Deception detection accuracy based on training condition and lie-type.

Mean accuracy (error bars ±1 *SE*) for emotion recognition training (ERT), bogus training (BT), and no training (NT) by video set, i.e., experiential (EXP) and affective (AFF), and veracity (Truth and Lie). The dashed line represents chance accuracy.

with Affective videos ($M = 48\%$, $SD = 13.6\%$). Similarly, there was a significant effect for lie judgements, $F(1, 103) = 4.00$, $p = .048$, $\eta_p^2 = .037$, 90% CI = [0.00, 0.11], JZS $BF_{10} = 1.37$, with Experiential videos ($M = 46.8\%$, $SD = 15.4\%$) being easier to detect than Affective videos ($M = 42.5\%$, $SD = 15.8\%$). Considering Veracity, simple effects revealed a significant difference between truths and lies for Experiential videos, $F(1, 103) = 71.43$, $p < .001$, $\eta_p^2 = .419$, 90% CI = [0.29, 0.50], JZS $BF_{10} = 2.0e^{12}$, as lies were harder to detect ($M = 46.8\%$, $SD = 15.4\%$) than truths ($M = 63.9\%$, $SD = 16.8\%$). Similarly, a veracity difference was found for Affective videos, $F(1, 103) = 7.45$, $p = .007$, $\eta_p^2 = .069$, 90% CI = [0.01, 0.16], JZS $BF_{10} = 8.89$, with lies ($M = 42.5\%$, $SD = 15.8\%$) being harder to detect than truths ($M = 48\%$, $SD = 13.6\%$) (see Figure 1).

Affective subsets: Emotional vs. unemotional. The accuracy difference between the two Affective subsets was also investigated. A three-way analysis was performed on the affective emotional (AE) and affective unemotional (AU) subsets to account for the type of emotion decoders saw. The results of the analysis of variance (ANOVA) revealed that the type of lie had a significant effect on accuracy, $F(1, 102) = 119.23$, $p < .001$, $\eta_p^2 = .539$, 90% CI = [0.52, 0.69], JZS $BF_{10} = 5.4e^{27}$, with AE videos showing higher accuracy ($M = 57.4\%$, $SD = 16.5\%$) than AU videos ($M = 31.9\%$, $SD = 12.9\%$). A main effect of Veracity was also observed, $F(1, 102) = 57.98$, $p < .001$, $\eta_p^2 = .297$, 90% CI = [0.18, 0.40], JZS $BF_{10} = 3.1e^{10}$, where truths were detected with higher accuracy ($M = 52.4\%$, $SD = 20.5\%$) than lies ($M = 37.0\%$, $SD = 21.9\%$). No effect of training or interaction was found, $Fs \leqslant 2.25$, $ps \geqslant .111$, JZS $BF_{10} < 0.9$.

Bayesian mixed-effects model. Given the potential variability in senders across the videos, an analysis is needed which can account for the sender–decoder variance. A

Bayesian mixed-effects model (BMEM) was used, using the *brms* package (Bürkner, 2018) in R 3.6.3 (R Core Team, 2020). Two models were constructed. The first (Null model) mirrored the linear analysis, with fixed effects for Training, Lie-type, and Veracity, and a random effect for participants. The second (Alt model) contained all elements of the Null model with the addition of a random effect for Stimuli, accounting for the variance introduced by the responses given to specific videos.[3] An advantage of BMEMs is their ability to cope with unevenness in the data, allowing us to run a single model comparing the three video sets directly (Experiential, Affective–Unemotional, and Affective–Emotional).

For each model, the β coefficients represent the median value of the posterior distribution of each parameter, and the corresponding 95% highest density interval (95% HDI) around this estimate, alongside a per parameter Bayes factor and Maximum Probability of Effect (MPE). For assessing model fit, we computed the leave-one-out (LOO) cross-validation and the Watanabe–Akaike information criterion (WAIC). To quantify the evidence in favour of the Alt model, a Bayes factor was calculated against the Null model (Table 1).

The values for the goodness of fit of the models are displayed in Table 2.

Based on the model fit statistics (Table 2) as well as visual inspection of the posterior predictive check (PPC) plots, the Alt model is superior to the Null model in explaining the data and predicting future data. As with the results of the ANOVAs, the data in Table 1 strongly favour no effect of Training on accuracy, regardless of Veracity or Lie-type. The addition of the Stimuli random effect in the Alt model resulted in slight changes in the estimations (Table 1), revealing that the difference in accuracy based on Lie-type is driven by the AU condition (EXP vs. AU, $\beta = -0.84$, 95% HDI = [−1.40, −0.28], $\delta_t = -0.97$, 95% HDI = [−1.65, −0.31]; AE vs. AU, $\beta = -1.25$, 95% HDI = [−1.97, −0.52], $\delta_t = -1.44$, 95% HDI = [−2.35, −0.58]) as decoders had poorer judgements in this condition. The Bayes factor indicates only anecdotal support for the weaker performance. Both models find the ubiquitous veracity effect, with overall higher truth detection. In the Alt model, however, the Bayes factor does not provide conclusive evidence for a veracity difference.[4]

Judgement confidence. An analysis considering the effect of Training and Lie-type on confidence revealed a main effect of Lie-type on confidence ratings, $F(1, 103) = 6.16$, $p = .015$, $\eta_p^2 = .056$, 90% CI = [0.01, 0.14], JZS $BF_{10} = 1.78$, but no main effect of Training, $F < 1$, $p = .579$, JZS $BF_{10} = 0.25$. The interaction was statistically significant, $F(2, 103) = 4.01$, $p = .021$, $\eta_p^2 = .072$, 90% CI = [0.00, 0.11], JZS $BF_{10} = 2.33$.

Simple main effects were conducted to unpack the interaction. With regard to Lie-type, a difference in confidence ratings was found between Experiential ($M = 63.41$,

Table 1. Parameter estimates, EE, 95% HDI, Bayes factor, and MPE ($N = 106$).

Model	Coefficient	Estimate	EE	95% HDI Lower	95% HDI Upper	BF_{10}	MPE (%)
Null model	**Intercept**	**−0.09**	**0.04**	**−0.17**	**−0.02**	**0.07**	**99.38**
	BT	−0.08	0.07	−0.21	0.05	0.01	88.56
	NT	−0.04	0.06	−0.17	0.08	$7.29e^{−3}$	75.27
	AU	**−0.79**	**0.07**	**−0.92**	**−0.66**	**$4.79e^{11}$**	**100.00**
	AE	**0.37**	**0.05**	**0.27**	**0.47**	**$5.69e^{4}$**	**100.00**
	Veracity (truth)	**0.49**	**0.05**	**0.39**	**0.58**	**$6.90e^{8}$**	**100.00**
	BT:AU	−0.14	0.12	−0.37	0.09	0.02	87.81
	NT:AU	−0.10	0.11	−0.32	0.12	0.02	81.17
	BT:AE	−0.06	0.09	−0.24	0.13	0.01	73.29
	NT:AE	−0.09	0.09	−0.26	0.09	0.01	83.85
	BT:Veracity	0.06	0.09	−0.11	0.23	$9.86e^{−3}$	76.27
	NT:Veracity	0.13	0.08	−0.03	0.30	0.03	94.28
	AU:Veracity	0.14	0.09	−0.04	0.32	0.03	93.02
	AE:Veracity	0.03	0.08	−0.12	0.17	$7.15e^{−3}$	63.19
	BT:AU:Veracity	−0.04	0.17	−0.37	0.29	0.02	59.20
	NT:AU:Veracity	0.16	0.16	−0.15	0.48	0.02	83.78
	BT:AE:Veracity	0.03	0.13	−0.24	0.29	0.01	58.00
	NT:AE:Veracity	−0.24	0.13	−0.48	0.01	0.07	96.89
Alt model	Intercept	−0.09	0.15	−0.39	0.20	0.02	72.62
	BT	−0.09	0.07	−0.24	0.05	0.01	89.58
	NT	−0.05	0.07	−0.18	0.09	$7.79e^{−3}$	73.98
	AU	**−0.84**	**0.28**	**−1.40**	**−0.28**	**1.67**	**99.77**
	AE	0.41	0.23	−0.05	0.88	0.10	96.09
	Veracity (truth)	**0.54**	**0.21**	**0.12**	**0.96**	**0.47**	**99.36**
	BT:AU	−0.15	0.12	−0.39	0.09	0.02	88.91
	NT:AU	−0.10	0.12	−0.34	0.13	0.02	80.61
	BT:AE	−0.07	0.10	−0.27	0.13	0.01	75.94
	NT:AE	−0.11	0.10	−0.30	0.08	0.02	86.92
	BT:Veracity	0.07	0.09	−0.11	0.25	0.01	77.22
	NT:Veracity	0.14	0.09	−0.03	0.32	0.03	94.90
	AU:Veracity	0.12	0.40	−0.67	0.91	0.04	62.47
	AE:Veracity	0.02	0.33	−0.63	0.67	0.03	52.73
	BT:AU:Veracity	−0.05	0.17	−0.39	0.29	0.02	61.02
	NT:AU:Veracity	0.17	0.17	−0.16	0.50	0.03	84.72
	BT:AE:Veracity	0.04	0.14	−0.24	0.32	0.01	61.34
	NT:AE:Veracity	−0.26	0.14	−0.53	0.01	0.08	97.13

EE: estimation error, 95% HDI: 95% highest density interval; MPE: Maximum Probability of Effect; BF_{10}: Bayes factor (Savage-Dickey density ratio) calculated as evidence for the Alt model relative to the Null model. BT: bogus training; NT: no training; AU: affective unemotional; AE: affective emotional. Bold represents parameters whose 95% HDI does not cross 0; if the Credible Interval passes 0, the parameter can be seen as non-significant / too uncertain.

Table 2. Goodness-of-fit measures, pseudo-R^2, LOO, WAIC, and Bayes factor (BF_{10}).

Model	R^2	LOO	WAIC	BF_{10}
Null model	$.08_{[0.06, 0.09]}$	2,798.6	2,798.6	−
Alt model	$.19_{[0.17, 0.21]}$	2,556.2	2,556.2	$5.19e^{90}$

LOO: leave one out; WAIC: Watanabe–Akaike information criterion; BF_{10}: Bayes factor (Savage-Dickey density ratio) calculated as evidence for the Alt model relative to the Null model.
Smaller LOO or WAIC values indicate a better model fit.

$SD = 8.31$) and Affective ($M = 67.13$, $SD = 8.01$) videos in the ERT group, $F(1, 103) = 10.85$, $p = .002$, $\eta_p^2 =$ .095, 90% CI = [0.02, 0.19], JZS $BF_{10} = 15.20$. Similarly, there was a difference between Experiential ($M = 61.97$, $SD = 10.30$) and Affective ($M = 65.07$, $SD = 10.11$) videos in the Control group, $F(1, 103) = 5.38$ $p = .028$, $\eta_p^2 =$ .050, 90% CI = [0.00, 0.13], JZS $BF_{10} = 2.06$. No effect occurred for the BT group, $F < 1$, $p = .483$, JZS $BF_{10} = 0.29$. With regard to the interaction based on Training, no differences were found for either video set, $Fs \leqslant 1.85$, $ps \geqslant .163$, JZS $BF_{10} < 0.39$.

Judgement bias. Investigating the effect of training on response bias did not reveal an effect of Training or Lie-type, $Fs < 1$, $ps \geqslant .431$, JZS $BF_{10} < 0.18$, or their

interaction, $F(1, 103) = 1.59$, $p = .210$, JZS $BF_{10} = 0.30$. Participants were overall truth-biased in their responses to both the Experiential videos ($M = 3.41$, $SD = 4.09$), $t(105) = 8.61$, $p < .001$, 95% CI = [2.63, 4.20], $d = 1.67$, JZS $BF_{10} = 3.0e^{10}$, and the Affective videos ($M = 3.08$, $SD = 5.38$), $t(105) = 5.88$, $p < .001$, 95% CI = [2.04, 4.11], $d = 1.15$, JZS $BF_{10} = 2.4e^5$.

Discussion

Study 2 tested the effect of emotion recognition training on veracity judgements. There was no effect of training compared with NT, nor any difference in judgements between ERT or BT. These findings align with recent critiques of the EBA arguing that a focus on emotional information may not be an optimal strategy (Burgoon, 2018; Hartwig & Bond, 2014; Jordan et al., 2019; Zloteanu, 2020). While accuracy did not improve, the fact that there was no further decline in accuracy is also noteworthy as past interventions have yielded negative outcomes after training (Levine, 2014a).

Most importantly, training did not affect confidence, although a positive trend was observed. This is interesting given that training typically bolsters people's already high confidence levels (DePaulo & Pfeifer, 1986). Perhaps the detection task was considered difficult and training did not ease the process sufficiently, thereby tempering confidence. Overall, decoders were found to be truth-biased which is consistent with the majority of research (Levine et al., 1999). Decoders also remained truth-biased in the training conditions, contrasting research showing that training reverses the decoder bias (Kim & Levine, 2011).

The use of multiple types of lies provides a comparison of decoders' veracity judgements across situations. The BMEM revealed that judgement differences were driven by AU lies and truths being more difficult to judge compared with both AE and EXP sets, suggesting that emotionality influenced decoders. Specifically, when the emotions were disingenuous, decoder accuracy was hindered, presenting a novel view of how lie-type affects judgement.

A few limitations need to be mentioned. First, while we consider the METT and SETT to be appropriate for emotion recognition training, there was no direct pre- and post-training measure of classification performance. As such, we cannot assess the impact of the ERT on recognition rates; this also prohibits us from analysing the relationship between ERT and lie-types (e.g., how SETT scores correlate with emotional lie detection as in Warren et al., 2009). Nonetheless, our protocols mirror the standards in the field (e.g., Jordan et al., 2019; Warren et al., 2009), employing tools which produce reliable effects (e.g., Hurley, 2012; Matsumoto & Hwang, 2011; McDonald et al., 2018). Second, the videos were not coded for emotional cues, nor did we question decoders whether they had relied on such information given that self-reports rarely provide accurate insights into judgement processes. Third, the valence of the AE set may have contributed to the pattern of results. When investigating multiple types of emotional lies and valence, Soppe (1988) similarly showed that simulations of negative emotions are more difficult to detect than suppressed emotional reactions, with simulations of positive emotions being easier to detect. Consequently, the valence of the emotion to be simulated may play a role in judging veracity (see also Barrett, 1998). It falls to future research to consider these possibilities further.

General discussion

The present work examined how judgements of veracity vary with the ability to perceive and understand others' emotional displays and/or the knowledge of emotional cues. Study 1 investigated the relationship between individuals' emotion recognition ability and veracity judgements. Contrary to the EBA, which predicts a positive association, we found that emotion recognition resulted in poorer deception detection. Such a result would be unexplainable using the accuracy-based approach, yet it is congruent and fully interpretable in terms of veracity judgements. As such, the negative correlation between accuracy and empathy suggests that high empathy may hinder decoding, potentially due to the misinterpretation of deceptive emotions as being genuine (e.g., Baker et al., 2013; DesJardins & Hodges, 2015; Israel et al., 2014). Alternatively, less empathic individuals may have an advantage in judging veracity as they potentially utilise cues, weigh information, and/or judge statements differently, leading to better accuracy (e.g., relying more on content). Results further showed that accuracy for detecting subtle and microexpressions was generally high, suggesting that people are capable of accurately perceiving and interpreting such brief cues, but this was unrelated to judgement accuracy.

A speculative explanation for how empathy and emotion recognition relate to veracity judgements comes from work on embodied cognition. It has been argued that decoders understand the affective state of others by simulating their expressions (Niedenthal et al., 2010). The sender's facial expression triggers similar facial responses in the observer (i.e., facial mimicry; Hess & Fischer, 2013), inducing the same affective state (i.e., leading to emotional contagion; Mafessoni & Lachmann, 2019). Hence, genuine and deceptive expressions should produce different activation patterns in the mimicker (i.e., reliable muscles). However, research does not find strong support for such differences (Krumhuber & Manstead, 2009), nor are decoders capable of discriminating emotion authenticity (Zloteanu et al., 2018, in press). Liars might produce deceptive emotional displays that are "good enough" to mislead decoders into inferring they reflect genuine affect.

It is then feasible to assume that empathy merely lowers the threshold for classifying emotional cues as a specific

emotion. Research finds that empathy relates to the speed of facial processing rather than the accurate classification of emotions (Kosonogov et al., 2015). In a nondeceptive scenario, this may result in more successful social interactions as empathics are quicker to react to the emotional state of others (Jani et al., 2012). However, empathy may impede accuracy in deceptive scenarios as decoders are less critical of emotional information, thereby misinterpreting cues.

When considering decoder knowledge of emotional cues, Study 2 found that the manipulation of emotion recognition ability in the form of training does not aid deception detection. This finding has important implications for forensic programmes that propagate the presence of emotional cues for lie detection (e.g., Inbau et al., 2011). Even if training can improve decoders' knowledge of facial cues (Matsumoto & Hwang, 2011), we think it would be insufficient to improve veracity judgements given people's low ability in distinguishing genuine from deceptive displays. Also, individuals may not be able to use the learned cues as these conflict with their heuristics and stereotypical beliefs about deceptive cues (Forrest et al., 2004). While the current findings do not exclude the possibility of other types of training aiding detection, there is no current support for the EBA's proposed relationship between emotion recognition and deception detection.

The goal of the present research was not to test a novel method for detecting deception based on emotional cues (as we have argued, this is not an empirically supported position) but to understand how reliance on emotional information affects human veracity judgements. The absence of a training effect (as evidenced by the Bayes factors) is fully expected given the lack of diagnosticity of emotional cues and their rarity in real-world scenarios. However, the role of emotionality (as evidenced by the different types of lies) corroborates our argument that emotions can affect judgement. Specifically, AU lies were harder to detect than AE lies, replicating the findings of Warren et al. (2009).

To explain this finding, it is important to consider the type of emotions in each scenario. While the emotional context was identical for AE and AU videos, senders in the AE condition were watching an emotion-evoking video. Reclassifying the emotional lie videos as *genuine emotional cues* (i.e., leaked disgust) and the unemotional lie videos as *deceptive emotional cues* (i.e., fabricated disgust) may help explain the difference in accuracy. If senders can produce genuine-looking displays (Krumhuber & Manstead, 2009) and decoders are poor at separating emotional authenticity (Zloteanu et al., 2018), then being emotionally perceptive is useful for detecting genuine emotions but detrimental for detecting deceptive emotions.

The current article also illustrates the need for deception research to consider multiple lie scenarios in decoder judgements. While the issue of reliability and generalisability has been broached in the past, it still has not been

fully addressed. Tasking decoders to judge various lie scenarios allows for a more complex understanding of differences (e.g., overall accuracy) and similarities (e.g., veracity effects) in performance.

With the BMEM we were able to analyse all three lie-types together and account for the variance introduced in the data by individual senders and decoders. Indeed, the Alt model explained more of the variance in the data and performed better at predicting veracity judgements, illustrating the importance of considering sender–decoder variability. The analysis confirmed that experiential lies (and truths) were detected at similar levels to AE lies, and both more accurately than unemotional lies. This indicates that unemotional lies were driving the difference, supporting our prediction of decoders being misled by deceptive emotional information when making veracity judgements.

Interestingly, the BMEM revealed that the veracity effect is less pronounced (and more uncertain) when accounting for the variability in responding to specific stimuli. This may imply that veracity effects observed in the literature are substantially affected by the judgement towards specific senders such as a demeanour bias (Levine, 2016). Hence, a response bias (i.e., truth-bias) or an adaptive response strategy (Street, 2015) may not (fully) account for veracity-specific accuracy rates. Given this pattern of results, we recommend that more attention should be given to both stimulus (sender) and decoder variability.

Together, findings from both studies support our assumption that decoders may be poor at discriminating authentic and deceptive emotional information. We suggest that research on emotion recognition separates *classification accuracy* from *authenticity discrimination* (see Zloteanu et al., 2018). Decoders clearly use emotion-related information (diagnostic or otherwise) for veracity judgements; however, contrary to previous propositions, they do not benefit from focusing on such cues. If decoders cannot separate *deceptive* from *genuine* emotional cues, their ability to detect them will unreliably relate to detection performance. At present, little is known about how people determine emotional authenticity (Kappas et al., 2013; Krumhuber et al., 2014). Failing to account for decoders' ability to discern emotional authenticity will produce mixed results, simply reflecting the stimulus type being utilised rather than the effectiveness of training or individual performance.

Limitations

Emotion recognition is a multifaceted construct, with facial cue detection and empathy being only two aspects. Our findings are limited to the current approach. Measures that capture other dimensions such as emotional intelligence (EI; Wojciechowski et al., 2014) may show additional effects. Furthermore, judging emotion recognition based on static facial displays may not capture the full ability of decoders (Zloteanu et al., 2018). Further research

should consider other modalities, such as vocal emotions (McKeown et al., 2014) and body expressions (Van den Stock et al., 2007).

Another consideration is the training method employed. While our methodology reflects an often-used approach in emotion-based deception detection research, it is not the only one. Two recent meta-analyses on deception detection training yielded that accuracy is moderated by the training being used (Driskell, 2012; Hauch et al., 2014). Interestingly, Driskell (2012) found that training containing (but not limited to) facial expressions produced the highest effect, while Hauch et al. (2014) found that training containing verbal cues, not nonverbal, was the most effective. Training length may also be a factor, with longer sessions producing different results (e.g., Porter et al., 2010).

Another factor relates to the generalisability of decoder judgements to other types of lies. Presently, experiential and affective lies were used based on our research aims. However, other lies may produce different results, such as sanctioned vs. unsanctioned lies (Sporer & Schwandt, 2007) or transgressions vs. opinions (Matsumoto et al., 2014), as is the role of stakes (Frank & Ekman, 1997) or motivation (Forrest & Feldman, 2000). It is important to note though that respective moderators have not been found to consistently affect veracity judgements (Driskell, 2012; Hartwig & Bond, 2014; Hauch et al., 2014), even when adopting approaches similar to ours (Jordan et al., 2019); also, detection ability seems to generally be stable (Hartwig & Bond, 2014).

Future directions

Expansions of the current work should target additional individual characteristics known to relate to emotion recognition, deception ability, and/or interpersonal sensitivity (e.g., Hall et al., 2009). These may concern age and gender effects on emotion recognition and expression (for a recent meta-analysis, see Gonçalves et al., 2018). For example, Ruffman et al. (2012) reported that older decoders perform more poorly than younger decoders at detecting deception, potentially due to the slower processing of brief facial cues. Contrary to our findings, they showed a positive relation between emotion recognition and overall deception detection ability. This may partly be explained by using opinion lies as stimulus material and by not accounting for response bias in their analyses. Nevertheless, such work adds to the body of research linking emotion recognition and veracity judgements.

Future studies might want to focus on differences in senders and the sender–decoder interaction. For this, work by Riggio and colleagues (Riggio et al., 1987; Riggio & Friedman, 1986) on social skills and deception ability may be useful in constructing a bidirectional and interactive approach (as with IDT). His research details the role of communication skills, emotional control, expressivity, and

emotion sensitivity in the deception and detection process. It corresponds with our supposition that poor veracity judgements based on emotional information are partly due to liars producing genuine-looking emotional displays that fool decoders (Zloteanu, 2015; Zloteanu et al., 2018) and certain senders being more/less believable (i.e., a demeanour bias; Riggio & Friedman, 1983).

While ecological validity was a consideration in the present research, the methodology used here is not the only option to understand the emotion–deception relationship. Our focus was on human veracity judgements; nonetheless, computer-based approaches may be more beneficial to answer whether it is possible to detect deception from emotion-based information. The current findings may be compounded by extraneous factors brought about by human detection such as perceptual or processing limitations and judgmental biases. However, such research must have strong theoretical and empirical foundations (Jupe & Keatley, 2020; Zloteanu, 2020).

Conclusion

In conclusion, emotions play a complex role in deception. Facial cue detection was not found to aid deception detection, while empathy was negatively related to accurate veracity judgements. Training in emotion recognition did not yield any improvements for either experiential or affective lies, nor did it result in more biased or overconfident judgements. While emotionally charged lies are argued to be easier to detect, here it was the experiential lies that had the highest accuracy. Nonetheless, emotions do influence detectability as AU lies were the hardest to judge, suggesting that decoders may struggle to utilise emotional information when making veracity judgements due to difficulty in discriminating genuine from deceptive emotional cues. As an alternative to traditional accuracy-based approaches, the present research demonstrates that a shift towards veracity judgement is more theoretically sound and compatible with empirical findings. This allows for the interpretation of improbable relationships under the EBA (such as the lack of positive effects of training or empathy) by considering the mental processes, biases, and limitations of human judges.

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Notes

1. DesJardins and Hodges (2015) did not measure empathy explicitly, but simply compared the ability of interaction partners to match their perception of a scenario with the intention of their partner.
2. Due to incomplete data, one participant was removed from the Subtle Expression Training Tool (SETT) analyses. The sample for these analyses is $N = 40$ (14 males).
3. A third, more maximal, model with random slopes for Stimuli by Type and Type by Participant was considered; however, this posed convergence issues, which after being resolved was found to only introduce more complexity with no benefit to estimation over the Alt model (ΔWAIC = −6.1; Bayes factor in favour of the simpler model, $BF_{01} = 786.35$).
4. In Bayesian mixed-effects models (BMEMs), Bayes factor estimates can be unreliable unless very large sampling is conducted and there are sufficient data; hence, these should be interpreted with caution.

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