When the Body Does Not Know: Bodily responses show the same poor lie–detection performance as explicit judgments in the data of Gunderson, ten Brinke, and Sokol-Hessner (2023)

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Volker H. Franz[*], Sascha Meyen[†], Ulrike von Luxburg[‡]

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Open Practices: Analyses were implemented twice independently (by VF and SM). Link to open methods: https://osf.io/de2nj

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Correspondence: should be addressed to:
Prof. Dr. Volker Franz; University of Tübingen; Department of Computer Science; Experimental Cognitive Science; Sand 6; 72076 Tübingen; Germany
Web: http://www.ecogsci.cs.uni-tuebingen.de
Email: volker.franz (at) uni-tuebingen.de

[*]Department of Computer Science, University of Tübingen, Tübingen, Germany
[†]Department of Computer Science, University of Tübingen, Tübingen, Germany
[‡]Department of Computer Science and Tübingen AI Center, University of Tübingen, Tübingen, Germany

Abstract

Gunderson, ten Brinke, and Sokol-Hessner (Personality and Individual Differences, *204*, 2023; henceforth: GBH) reported that persons who had perfect interoception of their bodily reactions could detect liars with an accuracy of up to 68% — far exceeding the 50% predicted by chance and well above what participants achieved in explicit, conscious judgments. GBH conclude that the body knows whether somebody is lying, although humans fail to leverage this knowledge in their explicit judgments. Because GBH used videos of true murderers lying about their deeds, the study has high practical relevance. GBH base their arguments on an upper bound introduced in this literature by Franz & von Luxburg (Psychological Science, *26*, 2015). However, they misinterpret the meaning of this upper bound and therefore come to overly-optimistic estimates of lie–detection accuracy. Reanalysis of their data with appropriate methods shows that the bodily reactions only allowed close–to–chance lie–detection accuracy, similar to participants' performance in explicit judgments. We conclude that GBH do not provide evidence for appreciable lie-detection capability in bodily reactions. Quite to the contrary, the study demonstrates how difficult it is to detect a liar — even if a real–world, high stakes scenario is used.

Keywords: deception, lie-detection, interoception, unconscious processing, statistical learning.

1 Introduction

GBH[1] used a high–stakes, real–world scenario to investigate human lie–detection. They presented 12 videos of individuals appealing via TV for help with finding a missing relative. Half of those individuals were later found guilty of being the murderers of this relative. Assuming that these guilty verdicts were justified (ten Brinke, Lee, & Carney, 2019, p. 564), these murderers were blatantly lying in one of the most existential ways one can imagine. Participants watched the videos and simple bodily reactions were measured (pulse plethysmography: PPG, and electrodermal activity/skin conductance level: SCL). GBH report that “participants could achieve an average of 68% accuracy” (p. 4) in detecting those liars had they only made “optimal use” (p. 5) of the measured bodily reactions. This would be a dramatic improvement over what participants could consciously report: Even with the strong and ecologically valid stimuli of GBH, participants were only 54.9% correct when directly asked who was lying — perfectly consistent with the famous 54% correct we know from the literature as the to–be–expected accuracy for conscious lie–detection (Bond & DePaulo, 2006). This conscious performance is so poor and so close to the chance–level of 50% that it has been dubbed lie–detection “incompetence” (ten Brinke, Stimson, & Carney, 2014; p. 1098).

In short, previous research tells us that humans are very bad at consciously detecting liars — not much better than guessing. In contrast, GBH claim that the body knows better whether somebody is lying and that “optimal use of [bodily] information would produce deception detection accuracy that far exceeded chance” (p. 5). If true, this could provide an exciting approach for solving the age–old problem of lie–detection incompetence in humans.

Unfortunately, GBH’s conclusions are erroneous. Their analysis is based on an argument introduced by Franz and von Luxburg (2015) in a critique of an earlier study (ten Brinke et al., 2014), but GBH misinterpreted this argument. To understand why, let us sketch the main lines of arguments involved: ten Brinke et al. (2014) had found significantly faster responses to pictures of liars than of truth–tellers (and vice–versa) and concluded that response times reflected “accurate” lie–detection (p. 1104); better than what participants can consciously report. However, ten Brinke et al. (2014) never had actually calculated accuracy and Franz and von Luxburg (2015) showed that they (as well as other studies) used inappropriate proxies to make inferences about accuracy. Instead—if one wants to make inferences about the underlying lie–detection accuracy—one needs to perform a classification and calculate accuracy (see also Meyen, Zerweck, Amado, von Luxburg, & Franz, 2022).

Franz and von Luxburg (2015) therefore reanalyzed the data of ten Brinke et al. (2014) and found that even with optimal classification schemes, response times only resulted in accuracies below the famous 54% correct for conscious lie detection (for more details see also Franz & von Luxburg, 2014). These poor accuracies conclusively showed that response times did not reflect accurate lie–detection. Nevertheless, and for good measure, Franz and von Luxburg (2015) did one more thing: To convince even a strong skeptic that there is nothing in these data, they showed that even an *upper bound* on classification accuracy in those data happens to be below the famous 54% correct.

This is where GBH come in: They focus exclusively on this upper bound (thereby ignoring the other classification schemes) and try to *invert* the direction of

[1]We abbreviate the original study (Gunderson, ten Brinke, & Sokol–Hessner, 2023) by GBH, pulse plethysmography by PPG, and electrodermal activity/skin conductance level by SCL.

this argument by assuming that the upper bound were the "optimal possible accuracy" (p. 4) if participants only made "optimal use of physiological signals" (p. 4). However, this is a serious misunderstanding of what an upper bound means. The upper bound only states that the to–be–expected accuracy *will be smaller* than the upper bound (Franz & von Luxburg, 2014, p. 12). The upper bound is not the ideally to–be–expected, "optimal possible accuracy" (GBH, p. 4).

1.1 Fallacy: GBH Confuse Training and Test Accuracy

Why does the upper bound not correspond to the to–be–expected accuracy under optimal use of bodily reactions? GBH constructed a classifier that uses the bodily reactions to discriminate between videos of liars and truth–tellers. Because during construction the full information of which videos showed liars was used, the accuracy on *those same videos* (which is called "training accuracy" in statistical learning) is an upper bound for what this *type of classifier* can achieve on those data. However, it is not the to–be–expected accuracy because during construction no true prediction was performed (all information about liars was available and used). Therefore, the training accuracy severely over–estimates the to–be–expected accuracy (e.g., Hastie, Tibshirani, & Jerome, 2009, chap. 7.4, James, Witten, Hastie, & Tibshirani, 2013, chap. 2). To estimate the to–be–expected accuracy, we need to use *new* videos and let the classifier predict whether they show liars. Only this "test–accuracy" is a sensible estimate of the to–be–expected accuracy when the classifier and the bodily reactions shall be used to detect liars.

Here in more detail: For each participant, GBH determined a criterion to decide whether the bodily reactions predicted a liar or a truth–teller. Videos arousing reactions smaller than this criterion were classified as liar (for PPG–measurements, cf. Table 1b). GBH tried all possible criteria and chose the "optimal criterion" (p. 4) that gave the highest accuracy for all 12 videos, which was then reported as being 68% correct. GBH went on to argue that "participants could achieve [this] accuracy on the deception detection task by relying on their PPG reactivity" (p. 4). However—as argued above—this training accuracy evaluates the criterion on the very data that was used to select the criterion. To assess the to–be–expected accuracy for future predictions, one has to evaluate the criterion not on the training data but on independent test data for which the true label was not already given when selecting the criterion. A typical approach would be to use some of the videos, say 10, to determine the criterion, and then use this criterion to detect liars in the remaining 2 "hold–out" videos. The accuracy on these hold–out videos provides unbiased estimates of the to–be–expected accuracy.

Now, the minor obstacle arises that this hold–out estimate is not very stable due to the relatively few data in GBH. The established solution is to repeat the procedure and average the results. Such a "cross–validation" provides more stable estimates (e.g., James et al., 2013, chap. 5). In our analyses, we therefore performed a cross–validation for all possible combinations of 10 training and 2 hold-out videos.

2 Methods

We reanalyzed the data of GBH (`https://osf.io/crqsk`). They used two conditions: Videos of pleaders (as described in the Introduction) and videos of a game–show. We analyzed both conditions and also both bodily reactions (PPG and SCL). In the following, we will focus on the classifiers used by GBH. Alternatively, one could also calculate sensitivities in a signal–detection framework, or use a median–classifier (Franz & von Luxburg, 2014, 2015; Meyen et al., 2022). Results are similar and can be found in our open methods. For brevity we will not report them here. All analyses were performed in R (R Core Team, 2021) and are publicly available via the Open Science Framework at `https://osf.io/de2nj`

3 Results

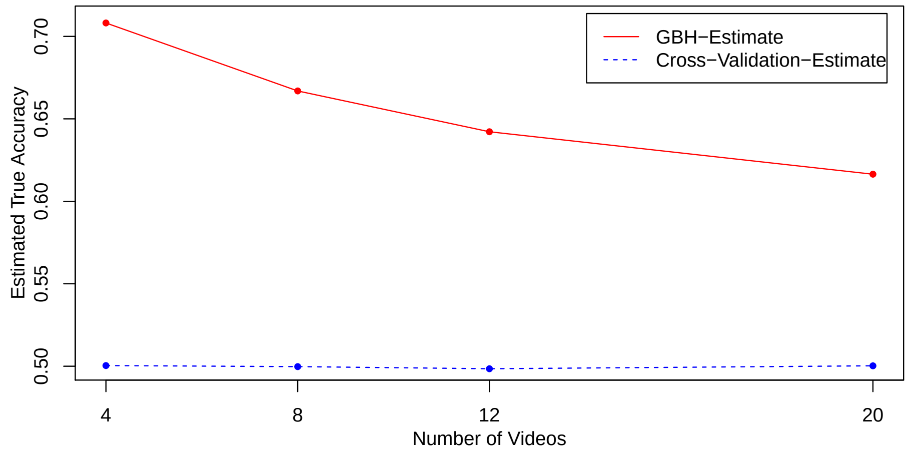
We use as shortcut names: **GBH–estimate** stands for the upper bound that was interpreted by GBH as the accuracy participants could achieve if they made "optimal use of physiological signals" (p. 4) and which corresponds to the training accuracy of the classifier. **Cross–validation–estimate** stands for the test–accuracy as estimated by cross–validation.

3.1 GBH–Estimate Heavily Overestimates Accuracy

We investigated what happens to the GBH–estimate if there were no lie–related information at all in the bodily reactions. To simulate this null–hypothesis, we drew the bodily reactions from exactly the same random distribution for videos of liars and truth–tellers (for N=62 simulated participants, as used by GBH) and trained a classifier in the same way as GBH did for their measured data. Because our simulated data do not contain any information about lying or truth–telling, an appropriate method should estimate chance–level accuracy (50%) as the to–be–expected accuracy of the classifier. As Figure 1 shows, this is so for the cross–validation–estimate but it is seriously violated for the GBH–estimate. The GBH–estimate reaches accuracy levels well above 60% for 12 and 20 videos—similar to the values GBH obtained for the corresponding number of videos with their bodily

Figure 1

Simulation of Null Hypothesis (No Lie–Related Information)



Note. Simulation of data containing no lie–related information. A valid estimation method for the to–be–expected accuracy of the classifiers should result in chance–level performance (50%). This is the case for the cross–validation–estimate, but is seriously violated for the GBH–estimate. This demonstrates that the GBH–estimate is not an appropriate estimator for the to–be–expected accuracy.

data (Table 1b/c). These simulations demonstrate that the GBH–estimate heavily overestimates the to–be–expected accuracy.

Figure 2 gives a worked example of why the GBH–estimate is so high, even though the simulated data do not contain any information about lying: Because the GBH–estimate uses the knowledge of which video showed a liar it can reach much higher accuracies than the to–be–expected accuracies for new videos, where we do not have this knowledge.

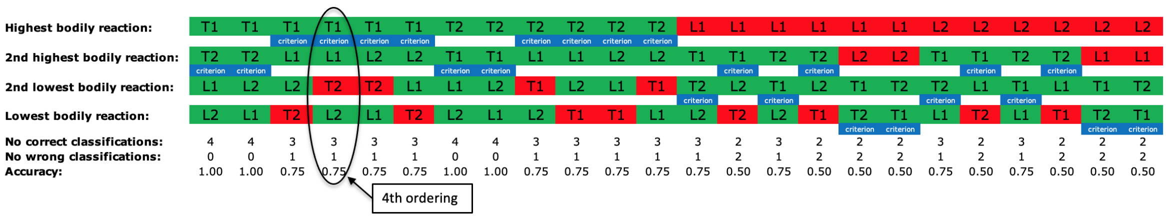
3.2 Bodily Reactions Show Lie–Detection Incompetence

Our simulations demonstrate that the GBH–estimate heavily overestimates the to–be–expected accuracy. This is so because the GBH–estimate (being the training accuracy) is contaminated by knowledge about who is lying. The cross-validation estimate, on the other hand, does not show these problems and provides a valid estimate of the to–be–expected accuracy. Therefore, we reanalyzed the bodily data of GBH and calculated the corresponding cross–validation–estimates. For all four conditions (2 types of videos $\times$ 2 types of bodily reactions), we found the cross–validation estimate to be below the famous 54% correct (Table 1b/c), and similar to what participants could explicitly report (Table 1a). Paired t tests of each cross–validation accuracy vs. the explicit judgment accuracy confirmed this (all $p > .15$). In short, the bodily data show a similar lie–detection incompetence as the explicit (conscious) judgments.

Now, one might ask whether more advanced classifiers than were used by GBH might improve accuracy. The bodily data of GBH were 2–dimensional (two responses were measured: PPG and SCL), but were only analyzed separately in a

Figure 2

Example: GBH–Estimate Overestimates Accuracy



Note. Example demonstrating why the GBH–estimate indicates high lie–detection accuracy, although the simulated data do not contain any information about lying. Consider four videos (2 liars / 2 truth–tellers). Each video induces a bodily reaction and we order the videos by this bodily reaction, such that each column shows one possible ordering. For each possible ordering the GBH–estimate determines the optimal criterion such that it maximizes accuracy for this specific ordering. For example, if we measured for a participant the 4th ordering, then the optimal criterion (shown in blue) would be between the bodily reactions to the video of truth–teller 1 (T1) and liar 1 (L1). This criterion would be successful in classifying the videos of T1, L1, L2 (green shading), but it would fail for T2 (red shading), resulting in an accuracy of 75% correct for this ordering. Because there is no information in the data about lying, each ordering is equally likely and we can average the accuracies across all orderings to obtain what is expected for the GBH–estimate. This gives an accuracy of 71% — well above the chance–level of 50%. This accuracy is also depicted in Figure 1 for four videos (where we used simulations to arrive at the same conclusion).

1–dimensional way. Could we improve accuracy by taking into account both reactions at the same time? We tested this possibility using well–established methods (James et al., 2013): (a) linear discriminant analysis (LDA), which can be interpreted as a generalization of the GBH classifier to higher dimensions (b) quadratic discriminant analysis (QDA), which imposes less strict assumptions than LDA on the variance/covariance–structure (c) k–nearest neighbors algorithm (KNN), which is a parameter–free method imposing minimal assumptions about the distributions underlying the data. Results show that even these methods can only produce cross–validation accuracies (Table 1d) at or below the famous 54% correct we know from the literature and similar to what participants could explicitly report (Table 1a). Paired t tests of each of these accuracies vs. the explicit judgment accuracy again confirmed this (all $p > .28$). Again, we find that the bodily responses show the same lie–detection incompetence as the explicit (conscious) judgments.

4 Discussion

No matter which classifier we used, the bodily data only allowed to–be–expected accuracies similar to the accuracies of the explicit judgments —and both were at the level of lie–detection "incompetence" (ten Brinke et al., 2014; p. 1098). This is in stark contrast to the conclusions of GBH and suggests that the body does not know when somebody is lying.

Before closing, let us clarify some potential sources of confusion: (a) Of course, we cannot conclude that *all* bodily reactions show the same lie–detection incompetence as the data of GBH. It is well possible that with more complex methods researchers might find bodily lie–detection capabilities. (b) We also cannot

Table 1

Accuracies Obtained by Different Classification Approaches

Accuracies in %		12 Pleader videos	20 Game–show videos
(a) Explicit (conscious) judgment		54.9 +/- 1.7	52.2 +/- 1.3
(b) PPG:			
	GBH–estimate	68.1 +/- 1.1	62.9 +/- 1.0
	Cross–validation–estimate	53.3 +/- 1.5	51.3 +/- 1.4
(c) SCL:			
	GBH–estimate	66.0 +/- 1.2	64.7 +/- 1.0
	Cross–validation–estimate	50.8 +/- 1.6	53.4 +/- 1.5
(d) PPG and SCL combined:			
	LDA cross–validation–estimate	53.2 +/- 1.9	53.4 +/- 1.8
	QDA cross–validation–estimate	53.7 +/- 2.1	54.0 +/- 1.7
	KNN cross–validation–estimate	52.8 +/- 2.0	53.7 +/- 1.8

Note. GBH–estimate: Reported by GBH as to–be–expected accuracies of the classifiers. This estimate heavily overestimates the to–be–expected accuracy. Cross–validation estimate: The appropriate method to estimate the to–be–expected accuracy. Explicit (conscious) judgment: Participants were asked who is lying; PPG: pulse plethysmography; SCL: skin conductance level; LDA: linear discriminant analysis; QDA: quadratic discriminant analysis; KNN: k nearest neighbors (KNN showed highest accuracy with k=1 for pleader videos and k=3 for game–show videos; these highest accuracies are given); all values are given as mean +/- standard error (calculated across participants).

conclude that there were no lie–related information in the videos. It is well possible that some advanced image processing software will find reliable cues to lie–detection in those videos. (c) An interesting question for future research will be how to match the task difficulty of the explicit judgment to that of the classifier evaluating the bodily responses. This is so, because the GBH setup actually made the task easier for the classifier. For example, during training of the classifier, the labels were perfectly reliable (i.e., there was no uncertainty whether a liar is really a liar) and the base rate of liars during training and test was exactly the same. Participants in their explicit judgments, on the other hand, had a much more difficult task to perform: They had no training with those videos. All they could do, was to rely on a life–long learning history of unclear labels (in daily life it is often unclear whether somebody is really lying) and the base rate of liars during this life–long learning likely did not match the base rate during the experiment. That is, the setup systematically advantaged the classifiers on the bodily reactions. This makes it all the more striking that those classifiers nevertheless could not beat the accuracy of the explicit judgments (see also the discussion of such issues in Meyen et al., 2022).

5 Conclusions

The GBH study has very nice and laudable aspects. For example, strong and ecologically valid stimuli were used and data and methods are openly available. Unfortunately, GBH mistook the training accuracy for the test accuracy. This statistical fallacy led to their overly optimistic conclusion that the body knows better when somebody is lying than what participants can explicitly (consciously) report. Instead, when applying appropriate methods, we find the famous deception–detection incompetence—even for the bodily responses.

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