Title: Use the best, ignore the rest: How heuristics allow to tell a lie from the truth

Authors: Bruno Verschuere^{1*}, Chu-Chien Lin¹, Sara Huisman¹, Bennett Kleinberg^{2,4}, & Ewout Meijer³

Affiliations:

¹Department of Clinical Psychology, University of Amsterdam

²Department of Methodology & Statistics, Tilburg University

³Faculty of Psychology and Neuroscience, Maastricht University

⁴Department of Security and Crime Science, University College London

* Corresponding author: BV. Email: b.j.verschuere@uva.nl

Abstract (current: 124 words; max 125 words): Could a simple rule of thumb help to find the truth? People struggle with integrating many putative cues to deception into an accurate veracity judgement. Heuristics simplify difficult decisions by ignoring most of the information and relying instead only on a few but highly diagnostic cues ('Use the best, ignore the rest'). We examined whether people would be able to tell lie from truth when instructed to make decisions based on a single, diagnostic cue (verifiability and richness in detail). We show that these simple judgements by lay people allowed to discriminate dishonest from honest statements. These judgements performed at or above state-of-the-art, resource-intensive content analysis by trained coders. For a tech- and training-free approach, heuristics were surprisingly accurate, and hold promise for practice.

One-Sentence Summary (current: 115 characters; max 125 characters): When relying on a single diagnostic cue to deception and ignoring all other cues, lay people's judgements allowed to tell lie from truth.

Main text (current: 986 words; max 2500 words):

Medical doctors, criminal court judges, HR consultants and stockbrokers all face a similar challenge: they need to make complex decisions in the face of substantial and often conflicting information – surgery or medication, guilty or innocent, hire or reject, buy or sell. One way of dealing with an information overload is to simply ignore most of it (1, 2). Consider a medical doctor who needs to decide whether a heart attack patient is best off with a regular nursing bed or the intensive care unit. Instead of considering all patient variables and medical test results, in order to be able to act promptly, the doctor may (need to) rely only on a few good cues. Such heuristics are not only efficient but can be surprisingly accurate as well. For classifying a heart attack patient, a simple decision tree with just three criteria outperformed algorithms that combined many parameters (1). Similarly - using just two criteria – age and criminal record – allowed to predict the risk of criminal recidivism with the same accuracy as an algorithm that combined 137 criteria (3). And a large-scale study on predicting life outcomes showed that complex computational models did not fare better than domain expert judgments based on just four variables (4). Sometimes, less is more.

One of the domains this 'less is more' principle may apply to is the difficulty lay people and experts face in telling lie from truth. Yet, being able to make a correct lie-truth judgment touches many areas of personal life (e.g., white lies in relationships), society (e.g., telling misinformation from actual evidence) and even the foundation of legal practice (e.g., detecting false testimonies and false confessions). The amount of information from which veracity

judgements can be derived is vast. When 138 police officers were surveyed about what could be good cues for lie detection, they mentioned 655 cues altogether (5). A meta-analysis mapping how predictive verbal and non-verbal behaviors are for deception, included no fewer than 158 cues (6). Most of these cues are not or only weakly related to deception, further adding to the complexity of veracity judgements. Unsurprisingly, when making veracity judgement, people struggle with integrating the different cues into a single veracity judgement, and perform at the chance level (7). Instead of considering all cues, the better strategy may be a simple heuristic: use-the-best (and ignore-the-rest) (1). Here, we introduce the use-the-best (and ignore-the-rest) heuristic to deception detection. Theory and meta-analytic reviews suggest that, when people describe an experienced event, richness in detail and verifiability are valid cues to deception (6, 8, 9). Could simple heuristics using only detailedness or verifiability allow ordinary people to tell lie from truth?

In a pilot (Study1), we found that considering a single, diagnostic cue (verifiability) allowed for accurate lie-truth discrimination. More so than when participants could consider any possible cues (veracity judgement), see Figure 1. The pilot inspired us to conduct three preregistered follow-up studies.

In Study2, participants evaluated alibi statements in which undergraduates – honestly or dishonestly – described their campus activities of the last 15 minutes. Truth tellers had just engaged in regular campus activities (e.g., call a friend, drink coffee), whereas liars had actually committed a mock crime: they had stolen an exam but falsely claimed innocent to have been doing campus activities. Two groups of crowdsourced participants evaluated only a single cue – either verifiability or richness in detail. The accuracy of their judgements was surprisingly high, confirming the use-the-best, ignore-the-rest heuristic applies to deception detection (see Table 1).

To replicate whether use-the-best judgements outperforms judgements that allow taking all possible cues into account we repeated study2 with twice the sample size to make sure we had sufficient statistical power (9; Study3). Again, we found the use-the-best heuristic to be surprisingly accurate (Cohen's $d_{\text{verifiability}} = 1.23$, Cohen's $d_{\text{detailedness}} = 1.15$), now also clearly outperforming the veracity judgements that allowed considering any possible cues ($d_{\text{deception}} = -0.10$). Moreover, Table 1 shows that the heuristics do better than the counting of details by trained coders – the manual procedure prevalent in research and practice that is much more recourse intensive.

To get an impression of classification accuracy, we used the average judgement for each of the 64 statements, for each judgement method, to predict statement veracity. The ROC analysis plots sensitivity against specificity and provides a measure of diagnostic value across all possible cut-off points. As shown in Table 2, classification accuracy (expressed as ROC a, ranging from the chance level of 0.50 to 1.00, perfect classification) was above chance for judgments relying on a single cue ($0.71 \leq \text{ROC a} \leq 0.75$; with the lower bound of the confidence intervals exceeding 0.50), but at chance level for veracity judgements that allowed considering any possible cues ($0.51 \leq \text{ROC a} \leq 0.61$; with the 95% confidence intervals including 0.50). Using Youden 's J (11), we identified the optimal cut-off point when equally balancing specificity and sensitivity. We used independent validation, the strictest method to avoid data overfitting. Hence, we used the data of Study2 to evaluate classification accuracy based on the optimal cut-off derived in Study3 (and vice versa). Accuracy was poor for veracity judgements (50-52%), but moderate (65-70%) for the single cue judgements, see Table 2.

In Studies 1 to 3, Dutch-speaking participants evaluated written Dutch statements. To avoid our findings would be specific to a single language or mode of production, we conducted a fourth study in which German-speaking participants evaluated interview transcripts in German, either on deception or on richness in detail. Again, participants struggled to tell lie

from truth even though they could consider all possible cues to deception. But when judging only a single-cue – and these judgements took on average only a minute – significant and large differences emerged between deceptive and honest interview transcripts.

When people could consider all possible cues to deception, they performed at chance level. This shows again just how challenging veracity judgements are. When people were instructed to consider only a single diagnostic cue, they could tell a lie from a truth. These judgements were quick and did not require any technology, practice, or training. Moreover, their accuracy was at or above that of the far more complex content-content coding of the statement. The current findings suggest a simple solution to a complex problem: a simple rule of thumb may help to find the truth.

References and Notes:

1. G. Gigerenzer, D. G. Goldstein, Gigerenzer, G., Todd, P.M., & the ABC Research Group. (1999). *Simple Heuristics That Make Us Smart* (1999).
2. A. Tversky, D. Kahneman, Judgment under Uncertainty - Heuristics and Biases Tversky Kahneman 1974. *Science* (80-.). (1974).
3. J. Dressel, H. Farid, The accuracy, fairness, and limits of predicting recidivism. *Sci. Adv.* **4**, 1–6 (2018).
4. M. J. Salganik, *et al.*, Measuring the predictability of life outcomes with a scientific mass collaboration. *Proc. Natl. Acad. Sci. U. S. A.* **117**, 8398–8403 (2020).
5. G. Bogaard, E. H. Meijer, A. Vrij, H. Merckelbach, Strong, but wrong: Lay people's and police officers' beliefs about verbal and nonverbal cues to deception. *PLoS One* (2016) <https://doi.org/10.1371/journal.pone.0156615>.
6. B. M. DePaulo, *et al.*, Cues to deception. *Psychol. Bull.* (2003) <https://doi.org/10.1037/0033-2909.129.1.74>.
7. C. F. Bond, B. M. DePaulo, Accuracy of deception judgments. *Personal. Soc. Psychol. Rev.* (2006) https://doi.org/10.1207/s15327957pspr1003_2.
8. T. J. Luke, Lessons from Pinocchio: Cues to deception may be highly exaggerated. 1–30 (2018).
9. M. K. Johnson, C. L. Raye, Reality monitoring. *Psychol. Rev.* (1981) <https://doi.org/10.1037/0033-295X.88.1.67>.
10. T. R. Levine, Y. Daiku, J. Masip, The Number of Senders and Total Judgments Matter More Than Sample Size in Deception-Detection Experiments. *Perspect. Psychol. Sci.* (2021) <https://doi.org/10.1177/1745691621990369>.

11. W. J. Youden, Index for rating diagnostic tests. *Cancer* **3**, 32–35 (1950).

Acknowledgements:

General: We thank Abdoullah El Feddali and Vittoria Giannelli for their help with the Pilot Study.

Funding: Ewout Meijer is supported by the Israel Institute for Advanced Studies.

Author Contributions:

Conceptualization: BV

Methodology: C-C L, SH, BV

Investigation: C-C L, SH

Writing – original draft: BV, EM

Writing – review & editing: BV, EM, BK

Competing interests: Authors declare that they have no competing interests.

Data and Materials availability: All data, materials, and analytic scripts are publicly available on <https://osf.io/z26ar/>

Supplementary Material

Study1 (Pilot)

Ethics approval, data, materials, and analysis scripts on <https://osf.io/z26ar/>.

Participants

51 undergraduates of the University of Amsterdam Psychology Department took part in Study1. We excluded 7 participants who failed the attention check (see below) and 5 participants who did not have Dutch as their mother tongue. Of the 39 remaining participants (31 female, 8 male; M age = 19.38 years, SD = 1.68), n = 19 judged deception (any cue possible) and n = 20 judged only the single cue verifiability. Participants received course credits for partaking in the study and the most accurate participant received a 20,- euro bonus.

Procedure

After providing online informed consent, participants were randomly assigned to the deception judgement or the verifiability judgement condition through Qualtrics. In both conditions, the participants were asked to evaluate 16 alibi statements, presented one by one, in a random order. In the verifiability judgement condition there was no mentioning of deception or lie detection.

Judging deception, participants were asked to evaluate “How truthful is this statement?”, on a scale from “totally deceitful” (-100) to “totally truthful” (+100), explaining that “A truthful statement is a statement that is true, honest and adheres to the fact of the situation”. Judging verifiability, participants were asked to evaluate “How verifiable is this statement?”, on a scale from “totally unverifiable” (-100) to “totally verifiable” (+100), explaining that “Verifiable activities are activities that are recorded (e.g. a security camera), documented (e.g. payment with a debit card or using a smartphone) or an activity with an

identifiable witness present”. This definition arose from the Verifiability Approach (10), but we simplified it to its essence for our purpose.

An attention check was embedded among the statements. It looked like another alibi statement but instructed participants to ignore the provided statement and instead answer -47 on the scale. After rating the (real and bogus) statements, a manipulation check asked participants about the basis for the judgments (indicate up to 3 out of the 11 cues from the list they used most as the basis of their judgement; with 3 cues referring to verifiability), a single item asked about motivation to accurately judge the statements (from -100 to +100), and finally participants were asked to provide age, gender, and mother tongue.

Materials

We used 64 alibi statements (32 truthful, 32 deceptive). To avoid item-effects, we created 4 sets of 16 statements (each containing 8 truthful and 8 deceptive statements), and participants were randomly assigned to receive one of the sets. The statements were selected from 72 statements obtained in a mock crime study where participants provided a handwritten statement on their whereabouts on campus in the last 15 minutes (11). Participants either truthfully described their activities, or they lied. The lying participants had just enacted the mock theft of an exam but pretended to have been on campus as a regular student. These statements were manually pseudonymized (i.e., all identifiable information including names of persons were changed to plausible alternatives). Content-coding by trained coders (11) showed that the 32 truthful statements ($M = 8.28$; $SD = 8.67$) contained more verifiable details than the 32 deceptive statements ($M = 3.47$; $SD = 4.65$), $d = 0.69$ (95% CI: 0.18; 1.19) (Table 2). Below is the English translation of one example statement (all original Dutch statements can be found on <https://osf.io/z26ar/>):

‘I quietly walked down until the entrance of G/lab. I was in doubt about what to do (stood still for a moment). Then I walked into the corridor of G, saw a cleaner/guy with a cart and read something about using lockers at the UvA. Then I walked to the outside entrance and walked around (back of G) and looked at the kind of butterflies that are now there for the light festival. So then walked further around G. Went back inside (second floor lab) and looked for a moment at university pabo, there is a poster next to the door about participating in brain research for money. When I had read that I walked quietly to this research room.’

Non-Confirmatory analyses

The 2 (Judgement Method: Deception vs Verifiability, between-subjects) x 2 (Veracity: Truthful vs Deceptive, within-subjects) mixed ANOVA on the participant’s judgment showed the predicted interaction effect between Judgment Method and Veracity, $F(1, 37) = 8.43$, $p = .006$, $\eta_p^2 = .19$ (Figure 1). To follow-up on the interaction, we conducted a paired sample t test contrasting judgements for truthful and deceptive statements within each judgement method. (Lie-truth differences when judging deception were small and non-significant, $t(18) = 0.45$, $p = 0.660$, $d = 0.10$ (95% CI: -0.35; 0.55)¹, $BF_{01} = 3.85$ ². In contrast, lie-truth differences when judging verifiability were significant and large, $t(19) = 4.00$, $p < .001$, $d = 0.89$, (95% CI: 0.36; 1.41), $BF_{10} = 45.65$.

Participants were motivated to provide an accurate judgement (Judging deception: $M = 66.32$; $SD = 29.48$; Judging verifiability: $M = 66.90$; $SD = 32.93$).

¹ Cohen’s d is the standardized mean lie-truth difference.

² The Bayes Factor BF_{01} expresses how much more likely the data are under the null hypothesis of no lie-truth difference than under the alternative hypothesis of a lie-truth difference. BF_{10} is the inverse of BF_{01} . We report BF_{10} when the data were more likely under the alternative hypothesis than under the null hypothesis.

The manipulation check showed that participants made judgements according to their instructions: Participants judging verifiability more often listed cues related to verifiability as the basis of their judgement ($M = 1.75$; $SD = 0.64$) than participants judging deception ($M = 0.68$; $SD = 0.75$), $t(37) = 4.78$, $p < .001$, $d = 1.53$, (95% CI: 0.81; 2.24), $BF_{10} = 669.50$.

Study2 and Study3

Ethics approval, data, materials, and analytic scripts of Study2 and Study3 can be found on <https://osf.io/z26ar/>. Moving from the exploratory stages of research to confirmation, we preregistered our hypotheses, analysis plan, and predictions, see also <https://osf.io/z26ar/>.

Method

There were a number of minor changes to Study1 procedure. There were now 3 conditions: Judging deception or making snap judgements based on either verifiability or detailedness. Also, we moved from locally recruited undergraduates to online crowdsourcing (Prolific.co participants with Dutch as first language; Paid 2.50£ for participation, with the 5 best performing participants receiving an additional 5.00£.), and provided participants during the initial instructions with a map of the campus. Aiming to avoid demand effects, we changed the manipulation check to an open box, asking participants to describe the cue they relied most on. We added a single item about experienced difficulty of the judgements (from -100 to +100). An additional attention question was added: After completing all judgments, a surprise multiple-choice question asked about the core of the last statement (e.g., finding a book). Demographics were obtained from Prolific.

Participants

Study2. 142 participants took part in Study2. We excluded 34 participants who failed either of the two attention checks³. The 108 remaining participants (39 female, 69 male; *M* age

³ Exclusion criteria were preregistered and served to assure that participants paid attention to each statement. But our findings do not hinge on the exclusion criteria. When not excluding any participant, the critical Judgment Method by Statement Veracity was significant for the combined data of Study1 and 2, $F(2, 441) = 32.68, p < .001, \eta^2_p = .13$. Moreover, there were

= 29.69 years, $SD = 10.34$; $n = 30$ judging deception, $n = 39$ judging verifiability, and $n = 39$ judging detailedness) mostly had the Dutch nationality (73%; Belgian: 24%; Other: 3%).

Study3. Participants from Study2 could not partake in Study3. 303 participants took part in Study3. We excluded 73 participants who failed either of the two attention checks. The 230 remaining participants (107 female, 119 male, 4 missing; M age = 30.32 years, $SD = 10.59$; $n = 77$ judging deception, $n = 89$ judging verifiability, and $n = 64$ judging detailedness) mostly had the Dutch nationality (72%; Belgian: 26%; Other: 2%).

Statistical Analyses

Confirmatory Analyses

Study2. Lie-truth differences when judging deception were small, $d = 0.39$ (95% CI: 0.02; 0.76), and lacked evidential value, $BF_{10} = 1.40$, but were just statistically significant, $t(29) = 2.14$, $p = 0.041$ (Table 1). In contrast, lie-truth differences when judging verifiability were again significant and large, $t(38) = 5.06$, $p < .001$, $d = 0.81$, (95% CI: 0.44; 1.17), $BF_{10} = 1854$. This was also true when judging detailedness, $t(38) = 6.61$, $p < .001$, $d = 1.06$, (95% CI: 0.66; 1.45), $BF_{10} = 173709$. However, the 3 (Judgement Method: Deception vs Verifiability vs Detailedness) x 2 (Veracity: Truthful vs Deceptive) mixed ANOVA only showed a main effect of Statement Veracity, $F(1, 105) = 53.03$, $p < .001$, $\eta^2_p = .34$, and not the predicted Judgement Method by Statement Veracity interaction, $F(2, 105) = 1.23$, $p = .297$, $\eta^2_p = .02$. Because the predicted interaction did not reach significance, we ran the study again, with more statistical power.

Study3. The 3 (Judgement Method: Deception vs Verifiability vs Detailedness) x 2 (Veracity: Truthful vs Deceptive) mixed ANOVA showed the predicted interaction effect, $F(2,$

large lie-truth differences for judging verifiability ($d = 0.95$) and detailedness ($d = 1.16$), but not for judging deception, $d = 0.06$.

227) = 31.84, $p < .001$, $\eta^2_p = .22$. Lie-truth differences when judging deception were small and non-significant, $t(76) = 0.86$, $p = 0.394$, $d = 0.10$ (95% CI: -0.13; 0.32), $BF_{01} = 5.60$ (Table 1). In contrast, lie-truth differences when judging verifiability were again significant and large, $t(88) = 11.60$, $p < .001$, $d = 1.23$, (95% CI: 0.95; 1.50), $BF_{10} = 2.56 \times 10^{16}$. This was also true when judging detailedness, $t(63) = 9.19$, $p < .001$, $d = 1.15$, (95% CI: 0.83; 1.46), $BF_{10} = 2.64 \times 10^{10}$.

Additional analyses

Because these analyses are highly similar for Study 2 and 3 (that used the same procedure), we aggregated the data of Study 2 and 3 ($n = 338$; results for each study separately can be found on <https://osf.io/z26ar/>).

Confirmatory additional analyses.

As a manipulation check of the judgment instructions, we coded the open box responses describing the cue that the participant relied most on. A condition-blind coder scored the responses as referring to verifiability, detailedness or other cues. Agreement with a second condition-blind rater was moderate to high (Study2, all statements double coded: 84% agreement; Study3, one third of statements double coded: 69% agreement). A Chi Square Test crossing Judgement Method (Judge Deception vs Judge Verifiability vs Judge Detailedness) with Reported Cue Use (Deception vs Verifiability vs Detailedness) indicated that participants reported using the cue they were instructed to use, $\chi^2(4) = 129.08$, $p < .001$, Cramer $V = 0.44$. Participants judging verifiability most often mentioned a cue related to verifiability (89%; Detailedness: 6%; Other: 5%). Participants judging detailedness most often mentioned a cue related to detailedness (44%; Verifiability: 28%; Other: 28%). Participants judging deception most often mentioned other cues (38%; Verifiability: 24%; Detailedness: 37%).

Non-confirmatory additional analyses.

Participants were motivated to provide an accurate judgement ($M = 76.99$, $SD = 23.89$; Judging verifiability: $M = 81.47$; $SD = 22.07$; Judging deception: $M = 75.49$; $SD = 22.19$; Judging detailedness: $M = 72.99$; $SD = 26.90$). Participants experienced the task to be moderately difficult ($M = 48.29$, $SD = 38.52$; Judging deception: $M = 58.75$; $SD = 36.43$; Judging verifiability: $M = 43.59$; $SD = 39.72$; Judging detailedness: $M = 43.27$; $SD = 37.27$).

Another way to examine what cues judges relied on, is to correlate their judgments with the content coding of trained coders. This correlational analysis also shows that people based their judgments on the cues they were instructed to use, see Table 3.

To examine agreement between judges, we calculated the ICC (Average Measure) per judgement method⁴. Since different judges rated different sets of statements, we calculated the ICC separately for each set of statements. We set negative ICCs to zero (1 out of 42 ICCs; occurring for deception judgements in Study4) (12). In Table 4, we report the ICC averaged across the sets of statements. Following interpretative guidelines (12), agreement between judges can be considered to be poor when judging deception, but strong when judging verifiability or richness in detail.

Robustness Analyses

Exclusion criteria were preregistered and served to assure that participants paid attention to each statement. But our findings do not hinge on the exclusion criteria. When not excluding any participant, the critical Judgment Method by Statement Veracity was significant for the combined Study 2 and 3 data, $F(2, 442) = 32.77$, $p < .001$, $\eta_p^2 = .13$. With large lie-truth

⁴ For Study1 (Pilot) the number of judges per series and method was well below recommended minimum number of judges ($k > 10$; LeBetron & Senter, 2008), so we refrain from reporting ICC for that study.

differences when judging verifiability: $d = 0.95$ or detailedness: $d = 1.16$), but not deception, $d = 0.06$.

Each participant judged one of 4 series of 16 alibi statements. Splitting the data per stimulus set (bottom rows Table 1) shows that the benefits of single-cue judgements do not hinge on a specific set of stimuli.

ROC Analyses

For each judgement method, we used the average statement judgement to predict statement veracity. The ROC analysis plots sensitivity against specificity and provides a measure of diagnostic value across all possible cut-off points. The area under the ROC curve varies from 0 to 1 (=perfect classification), with .50 denoting the chance level. As shown in Table 2, classification accuracy was above chance for judgments relying on a single cue (either verifiability or richness in detail), but at chance level for deception judgements.

Using Youden J , we also identify the optimal cut-off point when equally balancing specificity and sensitivity. We used independent validation, the strictest method to avoid data overfitting. Hence, we used the data of Study2 to evaluate classification accuracy based on the optimal cut-off derived in Study3 (and vice versa). Accuracy was poor for veracity judgements, and moderate for the single cue judgements, see Table 2.

Fig1. Average judgement of the truthful and deceptive statements when judging deception or verifiability in Study 1.

Table 1. Lie-truth differences (*d*; with 95% CI) when judging deception (all possible cues) or rather a single cue (verifiability or detailedness) for Study2 and 3.

	Single cue judgments			Content coding	
	Deception	Verifiability	Detailedness	Verifiability	Detailedness
Study2	0.39	0.81	1.06		
	(0.02; 0.76)	(0.44; 1.17)	(0.66; 1.45)	0.69	0.77
Study3	-0.10	1.23	1.15	(0.18; 1.19)	(0.26; 1.27)
	(-0.33; 0.12)	(0.95; 1.50)	(0.84; 1.47)		
Stimulus Set 1	0.49	1.47	1.49	1.14	0.78
	(0.06; 0.91)	(0.92; 2.02)	(0.89; 2.06)	(0.06; 2.19)	(0.25; 1.79)
Stimulus Set 2	0.09	1.63	1.23	0.44	0.50
	(-0.27; 0.46)	(1.12; 2.13)	(0.69; 1.76)	(-0.56; 1.42)	(-0.50; 1.49)
Stimulus Set 3	-0.01	0.82	1.64	0.55	1.59
	(-0.39; 0.37)	(0.40; 1.12)	(1.05; 2.22)	(-0.46; 1.54)	(0.43; 2.71)
Stimulus Set 4	-0.42	0.68	0.72	0.41	0.54
	(-0.81; 0.02)	(0.30; 1.04)	(0.30; 1.14)	(-0.59; 1.39)	(-0.47; 1.53)

Note. The four bottom rows show the data split per stimulus set (for Study 2 and 3 combined; to restrict loss of power). The last two columns show lie-truth differences obtained for content-coding by trained coders.

Table 2. Classification accuracy for deception, verifiability, and detailedness judgements for Study2 and 3

	AUC (with 95% CI)		Accuracy	
	Study2	Study3	Cutoff based on Study2 data, applied to Study3 data	Cutoff baseStudy3 data, applied to Study2 data
Deception	0.61 (0.47; 0.76)	0.53 (0.44; 0.62)	50%	52%
Verifiability	0.72 (0.61; 0.83)	0.75 (0.68; 0.82)	70%	69%
Detailedness	0.72 (0.60; 0.83)	0.71 (0.62; 0.80)	65%	67%

Table 3. Association between judgements (Study 2 and 3 data combined) and content coding of the statements

	Number of details (trained coder count)	Number of verifiable details (trained coder count)
Judging Detailedness	0.72***	0.33**
Judging Verifiability	0.07	0.65***
Deception judgment	0.00	0.36**

Note. Judgements from Study2 and 3 combined. Content coding from Verschuere et al 2021.

*** denotes $p < .001$, ** denotes $p < .01$, and * denotes $p < .05$.

Table 4. Agreement between judges (ICC) per Judgment Method.

	Judgment Method		
	Deception	Verifiability	Detailedness
Study			
Study2	0.31	0.87	0.86
Study3	0.58	0.92	0.90
Study4	0.39	N/A	0.86

Study4

Data, materials, and analytic scripts of Study4 can be found on <https://osf.io/z26ar/>. Hypotheses, analysis plan, and predictions were preregistered before the start of data collection, see preregistration on <https://osf.io/z26ar/>.

Method

Fluent-German crowdsourced-participants judged interview transcripts (see Materials) either on deception or on richness in detail⁵.

Participants

251 participants took part in Study4. We excluded 59 participants who failed both attention checks. The 192 remaining participants (92 females; M age = 27.59 years, SD = 9.11; n = 104 judging deception, n = 88 judging detailedness) were Polish (26%), German (13%) or had one of 27 other nationalities. Demographics were obtained from Prolific.

Procedure

After providing informed consent, participants were randomly assigned to the deception judgement or richness in detail judgement condition through Qualtrics. In both conditions, participants were asked to evaluate 13 transcripts (including one bogus transcript used as an attention check, but excluded from main analyses), presented one by one, in a random order. Instructions for the judgements were the same as for Studies 1 to 3.

⁵ To limit the required number of judges, we did not consider verifiability in Study4.

The first attention check concerned the bogus transcript, which looked like just another transcript, but with the instruction to ignore the transcript and instead answer -47 on the scale. The second attention check was a surprise recall test after the last transcript, asking to select a unique utterance (e.g., ‘forgot the name of the girl I was looking for’) in the last transcript from 6 options. Thereafter, participants rated motivation and difficulty, and were asked to list, one-by-one, the cues they had relied on.

Materials

We used 72 transcripts (half truthful, half deceptive). To avoid item-effects, we created 6 sets of 12 transcripts ⁶, and participants were randomly assigned to receive one of the 6 sets. The statements were selected from (13). Participants in that study were native-German speaking undergraduates who were interviewed about the two tasks they claimed to have been doing in the past half hour. Statements were later transcribed verbatim. We selected the transcripts from participants who had been instructed to consistently lie or tell the truth (i.e., the lie-lie and truth-truth conditions), and used only the ‘Find Michelle at the bus stop’ task. This task entailed leaving the lab, crossing the campus to the bus stop, try to find a girl named Michelle (of whom they received a photo), make notes of arriving and leaving buses and returning to the lab within 35 minutes. From the structured interview, we selected only the first response to the interviewer’s instruction to describe the task as accurately and in as much detail as possible. We edited the transcripts to correct for spelling errors, but we retained all utterances (e.g., ‘Ehm’). Content-coding of the entire transcripts by trained coders (13) showed that the 36 truthful transcripts ($M = 38.06$; $SD = 15.36$) contained more details than the 36 deceptive

⁶ Due to a programming error 1/6 series missed 1 (truthful) statement.

transcripts ($M = 25.72$; $SD = 9.66$), $d = 0.96$ (95% CI: 0.47; 1.45)⁷, see also Table 2. Below is the English translation of one example statement (all original German transcripts can be found on <https://osf.io/z26ar/>):

'Okay, so after I finished the task with the café I went to the stop at the hospital. I didn't know exactly where it was, so I first meandered through here a bit, asked 'uuh I'm doing a task, can you tell me where the stop is?' And I already thought that it was this one and then I went there. Yes, and then I was supposed to look for Michelle. There were two or three people sitting there, three people sitting there, and then I asked them in Dutch if their name was Michelle. Yes, there was no Michelle there, then I sat there for five minutes, looked to see if maybe some bus was coming by where a Michelle got off, but no bus came by at all. And then I came back here and, yes, I didn't complete the task because I didn't find Michelle'.

Statistical Analyses

Confirmatory analyses

The 2 (Judgement Method: Deception vs Richness in detail) x 2 (Veracity: Truthful vs Deceptive) showed the predicted interaction effect, $F(1, 190) = 20.09$, $p < .001$, $\eta^2_p = .096$. Lie-truth differences when judging deception were small and non-significant, $t(103) = 0.09$, $p = 0.929$, $d = 0.01$ (95% CI: -0.18; 0.20), $BF_{01} = 9.17$. In contrast, lie-truth differences when judging richness in detail were significant and moderate to large, $t(87) = 7.06$, $p < .001$, $d = 0.75$ (95% CI: 0.51; 0.99), $BF_{10} = 2.53 \times 10^7$.

⁷ Coders counted the number of perceptual, temporal, and spatial details, and we summed these to provide an index of richness in detail. Coding was based on the entire interview.

Non-Confirmatory analyses

Participants were motivated to provide an accurate judgement, $M = 52.92$, $SD = 39.05$ (Judging deception: $M = 51.78$; $SD = 41.30$; Judging richness in detail: $M = 54.28$; $SD = 36.39$) and rated the task moderately difficult, $M = 42.90$, $SD = 42.94$ (Judging deception: $M = 48.35$; $SD = 44.80$; Judging richness in detail: $M = 36.45$; $SD = 39.95$).

Tracking of the time spent per page⁸ showed that the average time to read and evaluate a transcript was about a minute, $M = 57.44$ sec., $SD = 30.81$ (Judging deception: $M = 58.80$ seconds; $SD = 33.82$; Judging richness in detail: $M = 55.82$ seconds; $SD = 26.92$).

Table 4 shows that agreement between judges was poor when judging deception and strong when judging richness in detail.

⁸ This Qualtrics feature was only implemented for Study4.