Taxing the Brain to Uncover Lying? Meta-analyzing the Effect of Imposing Cognitive Load on the Reaction-Time Costs of Lying


Published in:
Journal of Applied Research in Memory and Cognition

DOI:
10.1016/j.jarmac.2018.04.005

Citation for published version (APA):
Taxing the Brain to Uncover Lying? Meta-analyzing the Effect of Imposing Cognitive Load on the Reaction-Time Costs of Lying

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Lying typically requires greater mental effort than telling the truth. Imposing cognitive load may improve lie detection by limiting the cognitive resources needed to lie effectively, thereby increasing the difference in speed between truths and lies. We test this hypothesis meta-analytically. Across 21 studies using response-time (RT) paradigms (11 unpublished; total N = 792), we consistently found that truth-telling was faster than lying, but found no evidence that imposing cognitive load increased that difference (Control, d = 1.45; Load, d = 1.28). Instead, load significantly decreased the lie–truth RT difference by increasing the RT of truths, g = −.18, p = .027. Our findings therefore suggest that imposing cognitive load does not necessarily improve RT-based lie detection, and may actually worsen it by taxing the mental system and thus impeding people’s ability to easily—and thus quickly—tell the truth.

**General Audience Summary**
A popular idea in contemporary deception research is that lying is typically more difficult than telling the truth. People may therefore use cognitive effort as a cue for deception. Unfortunately, such cues are often faint. A novel technique to help lie detection is asking the interviewee to do an additional task (e.g., math exercises): liars would find such an additional task particularly debilitating because they are already investing cognitive effort in lying. We identified 21 studies that investigate this idea and statistically aggregated their results. An additional task did not increase lie–truth differences. In fact, imposing cognitive load made discriminating between lying and truth-telling slightly more difficult. We reason that imposing cognitive load may interfere with retrieving the truthful answer.

**Keywords**: Lying, Deception, Reaction time, Cognitive load, Honesty, Lie detection

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1 Shared first authorship.

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Lying often imposes greater mental demands than truth-telling. It can entail suppression of the truth, switching from the truthful narrative to a deceptive one, keeping the lie in working memory, or monitoring whether others believe the lie. Indeed, people often experience lying as being more difficult than truth-telling, and also experience the need to consciously suppress the truth when lying (Walczyk, Roper, Seemann, & Humphrey, 2003). Studies have employed a variety of methods to assess the cognitive processes associated with lying (Granhag, Vrij, & Verschueren, 2015), and of these, response times (RTs) have proven particularly useful. A recent meta-analysis of 114 studies (total N = 3307) found that responding with a lie takes longer than responding with the truth (Suchotzki, Verschueren, Van Bockstaele, Ben-Shakhar, & Crombez, 2017). This finding fits with the idea that lying typically requires greater mental capacity than truth-telling, and suggests that one can use RTs to detect lies. Indeed, some RT paradigms allow for differentiating between lies and truths well above chance levels (Verschueren & Kleinberg, 2016).

Based on a cognitive perspective of lying, Vrij, Fisher, Mann, and Leal (2006) propose that increasing people’s cognitive load (e.g., by asking them to do an additional task on top of being interviewed) will benefit lie detection: If people are under cognitive load and are trying to do two things at once, they will not have the mental capacity to lie effectively. This idea has attracted much scientific interest (Levine, Blair, & Carpenter, 2018; Vrij, Fisher, & Blank, 2017; Vrij & Granhag, 2012; Vrij, Meissner, et al., 2017). However, researchers have raised concerns that, by imposing cognitive load, honest people may also struggle to come up with true pieces of information (because they are also doing multiple things at once). Their difficulty in answering questions might mistakenly be seen as an indication of lying (Blandon-Gilin, Fenn, Masip, & Yoo, 2014). Moreover, liars might actually profit from being placed under cognitive load: they can divert their attention away from the challenging interview and their deceptive answers and focus instead on the secondary task (Ambach, Stark, Peper, & Vaitl, 2008). Indeed, doing mental math is an established strategy to beat the polygraph lie test (Honts, Devitt, Winbush, & Kircher, 1996), and lie–truth differences in RTs are smaller when processing of questions is more shallow (Suchotzki, Verschueren, Crombez, & De Houwer, 2013). These reasons suggest that imposing cognitive load does not necessarily help and could in fact hinder lie detection.

A previous meta-analysis (Suchotzki et al., 2017) estimated the size of the lie–truth difference in RT paradigms and argued that the large lie–truth differences support the cognitive theory of lying. The cognitive-load hypothesis states that imposing cognitive load will further increase the lie–truth difference.2 Because cognitive load may in fact have the undesirable consequence of reducing these differences, the current meta-analysis summarizes the present state of knowledge regarding the effect of cognitive load on the lie–truth difference in RTs.

### Method

#### Literature Search

We searched scientific databases (Web of Science and Google Scholar) using the following combinations of keywords: ["lying task" OR lying OR CIT OR "Concealed Information Test" OR "Sheffield Lie test" OR "autobiographical Implicit Association Test" OR "aIAT"] AND [deprivation OR depletion OR "cognitive load" OR intuition OR priming OR "time pressure"]. In addition, we searched the reference lists of a recent meta-analysis (Suchotzki et al., 2017), sent direct emails to researchers in our network, and put out a call for papers via several channels (mailing lists, Twitter, and Research Gate). By November 2017, we identified 21 studies (total N = 792) that met our inclusion criteria by (a) recording lie and truth RTs, within subjects, for at least 20 trials each, in a computerized task, and (b) including an experimental manipulation of cognitive load.3 Where necessary, we contacted the authors to obtain additional information. All included studies are marked with an asterisk (*) in the reference list. The relevant data from the included studies to reproduce our findings can be found at https://osf.io/a2twq/.

#### Lying Paradigm

Lie and truth RTs can be collected using one of several paradigms, most notably the RT-based Concealed Information Test (CIT; Seymour, Seifert, Shafto, & Mosmann, 2000), the autobiographical Implicit Association Test (aIAT; Sartori, Agosta, Zogmaister, Ferrara, & Castiello, 2008), and the differentiation-of-deception paradigm (DoD; Furedy, Davis, & Gurevich, 1988). We will illustrate how these paradigms measure truth and lie RTs with the case of false identity.

In the CIT, the participant is presented with an item that has special saliency (e.g., the participant’s first name, TWAN) among a series of irrelevant items (e.g., first names such as WISSE, TIES, MICHAEL, LUKA). The participant is instructed to press one (YES) button for a dedicated target stimulus only (e.g., RAMSES), and press the other (NO) button for all other stimuli. Participants in the CIT may be explicitly informed that a NO response to the salient stimulus is a lie and/or be asked to hide recognition of the salient information such that the NO

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2 The terminology in this field has been confusing, because “cognitive load” (Vrij et al., 2006) may refer to both the specific technique of imposing cognitive load as well as to the general cognitive theory of lying. The cognitive theory holds that lying is typically more effortful than truth-telling. The cognitive-load hypothesis refers to a specific prediction derived from the cognitive theory, namely, that increasing cognitive load (e.g., by asking to do an additional task) will amplify lie–truth differences.

3 Because RTs are noisy and have to be averaged across sufficient trials to provide a reliable and valid index of deception, and in line with Suchotzki et al. (2017), we excluded studies that did not have at least 20 lie and 20 truth trials (e.g., Ambach et al., 2008; Cheng and Broadhurst, 2005; Gawrylczek et al., 2016; Walczyk et al., 2003). We also excluded studies that used a correlational rather than an experimental design (e.g., Suchotzki et al., 2015). Furthermore, we excluded studies in which the cognitive-load manipulation was confounded with the lie/truth manipulation (e.g., Suchotzki and Gamer, 2017; Van Bockstaele et al., 2012; Verschueren et al., 2011). Our operationalization of cognitive load did not include brain-stimulation techniques (e.g., Fecteau et al., 2013; Karton and Bachmann, 2011) or faking strategies (e.g., Hu et al., 2012).
responses to the salient stimulus can be considered a lie. The NO responses to the irrelevant names are averaged to provide the truth RT.

The aAT measures the association between two mutually exclusive autobiographical statements (e.g., “My name is Twan” vs. “My name is Ramses”) and the labels TRUE and FALSE. The core idea of the aAT is that the speed of associating these statements with TRUE versus FALSE provides information on their veracity. For instance, when the participant is faster to pair “My name is Twan” with TRUE and “My name is Ramses” with FALSE than vice versa, one can infer the participant’s name is Twan.

The DoD presents the participant with a series of Yes/No questions (e.g., “Is your name Twan?”), along with a cue to answer some questions honestly and others deceptively (e.g., “Lie about your name, but not about your birthday”). In the present study, we did not differentiate between the DoD and a variant called the Sheffield Lie Test, where lie versus truth is manipulated for each question—for example, when the question is in blue, you tell the truth, and when in yellow, you lie (Spence et al., 2001)—rather than across questions as in the DoD.

Cognitive-Load Manipulation

We used a broad definition of cognitive load (Rand, 2016), including an additional task, time pressure, ego depletion, stress, sleep deprivation, and a foreign language. Although obvious differences exist between the manipulations, they have all been theorized to tax the participant’s executive functions.

As the name implies, the additional task manipulation requires the participant to perform an additional task (e.g., remember and later report a string of letters) on top of lying and truth-telling in the lying paradigm, and is arguably the most frequently used manipulation in the cognitive-load literature (Lavie, Hirst, De Fockert, & Viding, 2004; Murphy, Groeger, & Greene, 2016). When studies implemented several levels of load (e.g., high load vs. low load vs. no load), we selected the most extreme comparison for inclusion in our study (e.g., high load vs. no load in the example above). The foreign-language manipulation (Service, Simola, Metsânheimio, & Maury, 2002) presents the questions in a non-native language, with the native language serving as the control condition (e.g., Dutch students may be presented with questions in both English and Dutch, with the English questions serving as the cognitive load). Ego depletion (Baumeister, Bratslavsky, Muraven, & Tice, 1998) involves engagement in an effortful task (e.g., the Stroop task) before taking part in the lying paradigm, with the expectation that the prior engagement depletes the already-limited resources needed for exerting cognitive control during lying. Stress may also act as a form of cognitive load (Raes, De Raedt, Verschueren, & De Houwer, 2009), and we therefore included studies that induced negative emotionality as opposed to a neutral or positive induction. Because sleep deprivation can interfere with exerting effortful control (Drummond, Paulus, & Tapert, 2006), we included studies that experimentally induced sleep deprivation as opposed to regular sleep. Finally, a response deadline (Shalvi, Eldar, & Bereby-Meyer, 2012) may urge participants to answer rapidly, thereby limiting resource allocation in the lying paradigm, and is contrasted with no or a more lenient deadline.

Meta-Analytic Procedure

We subtracted the RT cost of lying for the control condition from that for the load condition. We then standardized this difference by dividing it by the standard error term that, for within-subject comparisons, was corrected for inter-correlation. We used the bias-corrected standardized difference, Hedges’ *g*, between the RT cost for the load condition versus the control condition as the effect size in our meta-analysis. Because of the small sample sizes, we relied on Hedges’ *g* rather than Cohen’s *d* (see Hedges, 1981, for more details). All formulae used in the meta-analytic calculations can be found on https://osf.io/a2twq/.

Using the software package Comprehensive Meta-Analysis (Borenstein, Hedges, Higgins, & Rothstein, 2009, Chapter 44), we chose a random-effects model to calculate the average effect of load on the RT cost of lying. A positive score implies that the RT difference between lying and truth-telling is amplified by load, as intended by the imposing-cognitive-load technique.

Results

Table 1 and Figure 1 show that only two studies found the expected result from the imposing-cognitive-load technique (a significant positive score, indicating that load amplified the lie–truth difference). Many studies (*n* = 11) showed no significant effect of load, and eight studies produced a significant negative score, indicating that load decreased lie–truth differences. Overall, the meta-analysis showed that cognitive load

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Table 1

<table>
<thead>
<tr>
<th>Study</th>
<th>Hedges’ <em>g</em></th>
<th>95% CI</th>
<th><em>p</em></th>
</tr>
</thead>
<tbody>
<tr>
<td>Williams, Bott, Patrick, &amp; Lewis, 2013; Exp3</td>
<td>0.75</td>
<td>[0.37, 1.00]</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Visu-Petra, Varga, Mielec, &amp; Visu-Petra, 2013</td>
<td>0.36</td>
<td>[0.13, 0.60]</td>
<td>0.02</td>
</tr>
<tr>
<td>Williams et al., 2013; Exp4</td>
<td>0.14</td>
<td>[−0.20, 0.47]</td>
<td>0.42</td>
</tr>
<tr>
<td>Debye, De Houwer, &amp; Verschueren, 2014; Exp2</td>
<td>0.10</td>
<td>[−0.17, 0.33]</td>
<td>0.46</td>
</tr>
<tr>
<td>Debye, Verschueren, &amp; Crombez, 2012; Exp2</td>
<td>0.09</td>
<td>[−0.20, 0.38]</td>
<td>0.53</td>
</tr>
<tr>
<td>Rowthorn, 2016; Exp1</td>
<td>0.09</td>
<td>[−0.22, 0.39]</td>
<td>0.58</td>
</tr>
<tr>
<td>Kleinberg et al., 2014; Exp1</td>
<td>0.08</td>
<td>[−0.33, 0.50]</td>
<td>0.69</td>
</tr>
<tr>
<td>Debye et al., 2014; Exp1</td>
<td>−0.03</td>
<td>[−0.40, 0.34]</td>
<td>0.88</td>
</tr>
<tr>
<td>Verschueren et al., 2015</td>
<td>−0.06</td>
<td>[−0.37, 0.24]</td>
<td>0.68</td>
</tr>
<tr>
<td>Chua, Nisbett, Buhle, Rice, &amp; Osherson, 2009</td>
<td>−0.07</td>
<td>[−0.29, 0.14]</td>
<td>0.50</td>
</tr>
<tr>
<td>Debye et al., 2012; Exp1</td>
<td>−0.10</td>
<td>[−0.33, 0.14]</td>
<td>0.43</td>
</tr>
<tr>
<td>Varga, Visu-Petra, Mielec, &amp; Visu-Petra, 2015</td>
<td>−0.18</td>
<td>[−0.46, 0.11]</td>
<td>0.22</td>
</tr>
<tr>
<td>Williams, 2012; Exp8</td>
<td>−0.26</td>
<td>[−0.71, 0.16]</td>
<td>0.22</td>
</tr>
<tr>
<td>Rowthorn, 2016; Exp2</td>
<td>−0.46</td>
<td>[−0.82, −0.11]</td>
<td>0.01</td>
</tr>
<tr>
<td>Williams et al., 2013; Exp5</td>
<td>−0.53</td>
<td>[−0.90, −0.15]</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Suchotzki &amp; Gamer, 2018; Exp1</td>
<td>−0.54</td>
<td>[−0.88, −0.22]</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Suchotzki &amp; Gamer, 2018; Exp3</td>
<td>−0.56</td>
<td>[−0.88, −0.25]</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Suchotzki &amp; Gamer, 2018; Exp2</td>
<td>−0.59</td>
<td>[−0.93, −0.25]</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Williams, 2012; Exp7</td>
<td>−0.63</td>
<td>[−1.10, −0.15]</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Hu et al., 2013</td>
<td>−0.92</td>
<td>[−1.34, −0.51]</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Kleinberg et al., 2014; Exp1</td>
<td>−1.12</td>
<td>[−1.77, −0.48]</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
led to smaller RT differences between lying and truth-telling, Hedges’ $g = -0.184$, $SE = 0.083$, 95% CI $[-0.35, -0.02]$, $Z = -2.22$, $p = 0.027$.

Additional meta-analyses per condition following Suchotzki et al. (2017) showed that the average lie effect (i.e., the standardized lie vs. truth difference) was large for both the control condition (Truth RT: $M = 1019$, $SD = 210$; Lie RT: $M = 1205$, $SD = 270$), Cohen’s $d = 1.45$, 95% CI $[1.23, 1.66]$, $p < .0001$, and the load condition (Truth RT: $M = 1054$, $SD = 213$; Lie RT: $M = 1201$, $SD = 256$), Cohen’s $d = 1.28$, 95% CI $[0.97, 1.59]$, $p < .0001$.

Note that the average effect is qualified by the observed heterogeneity in findings. We used Cochran’s $Q$ and $I^2$ to quantify the heterogeneity in effect sizes. The $Q$-value is 105.78 with $df = 20$ and $p < 0.0001$, indicating that the variance is unlikely to be solely due to sampling error. The $I^2 = 81.09$ indicates that approximately 81% of the observed variance is due to real differences between studies. Unfortunately, the number of studies was insufficient for moderation analyses. For exploratory purposes, we show the impact of cognitive load on lie–truth differences per load manipulation, lying paradigm, and within- versus between-subjects manipulation of load (Table 2).

These exploratory analyses showed the absence of any conditions under which the cognitive-load hypothesis was supported (the effect was never significantly positive). They further suggest that the detrimental effects of cognitive load (significant negative effect) may be most apparent when using a within-subjects manipulation of cognitive load and the non-native-language manipulation.

**Publication Bias**

Because of the large heterogeneity, inspection of the funnel plot is inappropriate and could lead to false positive results.
regarding publication bias (Ioannidis & Trikalinos, 2007; for a more detailed discussion regarding the present meta-analysis see https://osf.io/a2twq/). Furthermore, we could not run a p-curve analysis because the primary studies did not explicitly make predictions about the effect of interest on our meta-analysis, or were interested in additional moderators (Simonsohn, Nelson, & Simmons, 2014; see also http://www.p-curve.com/guide.pdf). Moreover, a p-curve analysis plots significant p-values only, and many primary studies found non-significant effects. This left us with a comparison of the average effect obtained in published versus unpublished studies (Table 2), which indicates that the detrimental effect of cognitive load is most apparent in unpublished work.

**Discussion**

Building on the cognitive theory of lying, Vrij et al. (2006) hypothesized that imposing cognitive load would make lying more difficult and would benefit lie detection. The current meta-analysis tested this hypothesis by assessing the efficiency of the cognitive-load technique in RT-based deception paradigms, based on 21 relevant studies. Our meta-analysis includes a balanced number of published and unpublished studies. We observed large lie–truth differences in RTs but saw no evidence that the imposing-cognitive-load technique would amplify these differences. By contrast, several studies found load significantly diminishes the RT signature of lying, and the average effect size across studies was negative. These findings fuel the concern that additional load may in fact hinder RT-based lie detection (Ambach et al., 2008; Blandon-Gilitin et al., 2014; Vrij & Fisher, 2016).

Detrimental effects of cognitive load were most apparent in unpublished work. One explanation may be that such studies are of lesser quality. The fact that three studies that were unpublished at the time of research (SG2016 Experiments 1–3) were accepted for publication in a prominent journal during finalizing the present paper (Suchotzki & Gamer, 2018) speaks against this possibility. Another explanation is that researchers may have been less likely to submit or journals less likely to accept findings that go against the dominant view. Whatever the explanation, we recommend preregistration (Nosek & Lakens, 2014) to ensure that unexpected findings also leave the file drawer and make it to the published literature.

Where do the obtained results leave us with regard to the cognitive theory of lying? Importantly, for both the control condition and the load condition, we found large lie–truth differences in RTs, replicating previous work (Suchotzki et al., 2017). Following the logic of mental chronometry (Donders, 1969), and given the time-pressure nature of the tasks (Shalvi et al., 2012), these findings support the basic premise that lying typically takes more cognitive effort than truth-telling. Meanwhile, we found no support for the specific imposing-cognitive-load technique aimed at hampering the more effortful task (lying) more than the less effortful task (truth-telling) to increase lie RTs more than truth RTs. We hypothesize that cognitive load can overload working memory and restrict people’s ability to quickly tell the truth (see also Vrij & Fisher, 2016). Although admittedly speculative, the following analogy may help explain why load affected truth RTs more than lie RTs: a fast car (the truth) gets you from point A (the question) to point B (the answer) more quickly than a slow car (the lie), but not in a traffic jam. In a traffic jam, both cars are equally slow. Imposing too much load may function like a cognitive traffic jam: If the situation becomes too demanding, you no longer tell the truth more quickly than you lie.

Given the theoretical and applied implications of this line of work, we think that pursuing it and further investigating the impact of load on ease of lying is important. Our meta-analysis provides important insights into how this endeavor should be undertaken. First, our findings suggest that the average effect may be small, calling for much larger sample sizes to reliably establish the impact of load. Second, because many studies showed null effects, firmly establishing that the load manipulation effectively taxed the participants’ mental capacities, particularly (but not only) for manipulations in which the effectiveness has been challenged (e.g., ego depletion; Hagger et al., 2016), is important. We also suggest assessing cognitive ability, because what is cognitively taxing varies widely for different people (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). Third, the observed heterogeneity calls for identification of conditions under which load may be helpful or in fact detrimental to lie detection. Our hypothesis that load may reduce the benefit of relying on the dominant truth response, as well as our exploratory analyses (Table 2), may guide this search. Fourth, even if load does not make lying itself more difficult, it may be of use for lie detection, either by hampering attempts to fake the lie test (Kleinberg, Suchotzki, Lettinga, & Verschuere, 2014) or by providing cues to deception when lying becomes apparent from decreased performance on the secondary task (Hu, Evans, Wu, Lee, & Fu, 2013; Vrij et al., 2006).

This study is not without its limitations. First, although we see sufficient communality, the appropriateness of aggregating quite diverse lying paradigms as well as quite diverse load tasks.
could be questioned. Second, although the available database allowed us to estimate the average effect of cognitive load on the RT signature of lying (Valentine, Pigott, & Rothstein, 2010), we were unable to run moderation analyses to grasp the observed heterogeneity. Third, most primary studies relied on predominantly young, female student samples, limiting generalizability to legal settings.

Our findings, and the cognitive-load literature at large, raise several questions that need to be addressed before the imposing-cognitive-load technique is used in practice: How much cognitive load enables efficient detection of lies? What type of cognitive load is most effective? That is, should we ask people to do two cognitive tasks at once, or add a physical task? Is imposing load equally effective when examining people from all walks of life, or does the effect of load depend on age, education, and cognitive ability? The consequences of lie detection are too great for these questions to remain unanswered.

**Conclusion**

Finding substantial lie–truth differences in RTs, our findings support the cognitive theory of lying. But our findings also show that, for the well-established RT index of lying, imposing additional load may in fact hinder truth-telling, to the extent that the differences between lying and truth-telling become less apparent.

**Conflicts of Interest Statement**

The authors declare no conflict of interest.

**Author Contributions**

All authors conceived the presented idea. With input from BV, NK coded the studies. With input from DR and BV, NK conducted the meta-analysis. All authors discussed the results. BV wrote the manuscript, and all authors provided input for the final version.

**Acknowledgments**

We would like to thank Isabelle van der Vegt for her aid in coding the studies, Raoul Grasman for his valuable suggestions on the meta-analytic strategy, Bobbie Goettler for APA editing, and Kristina Suchotzki and Gershon Ben-Shakhar for their helpful comments on an earlier version of this manuscript. Finally, we wish to thank the authors of the primary studies for providing us with their data and/or answering our questions; thank you Emma Williams, Hannah Faye Chua, Harriet Rowthorn, Laura Visu-Petra, Kristina Suchotzki, and Xiaqing Hu. This project has received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation program (grant agreement: ERC-StG-637915).

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Received 29 November 2017; received in revised form 26 April 2018; accepted 27 April 2018
Available online 5 June 2018