

# No conclusive evidence that difficult general knowledge questions cause a “Google Stroop effect”. A replication study

Guido Hesselmann<sup>Corresp. 1</sup>

<sup>1</sup> Department of General and Biological Psychology, Psychologische Hochschule Berlin (PHB), Berlin, Germany

Corresponding Author: Guido Hesselmann  
Email address: g.hesselmann@phb.de

Access to the digital “all-knowing cloud” has become an integral part of our daily lives. It has been suggested that the increasing offloading of information and information processing services to the cloud will alter human cognition and metacognition in the short and long term. A much-cited study published in *Science* in 2011 provided first behavioral evidence for such changes in human cognition. Participants had to answer difficult trivia questions, and subsequently showed longer response times in a variant of the Stroop task with internet-related words (“Google Stroop effect”). The authors of this study concluded that the concept of the Internet is automatically activated in situations where information is missing (e.g., because we might feel the urge to “google” the information). However, the “Google Stroop effect” could not be replicated in two recent replication attempts as part of a large replicability project. After the failed replication was published in 2018, the first author of the original study pointed out some problems with the design of the failed replication. In our study, we therefore aimed to replicate the “Google Stroop effect” with a research design closer to the original experiment. Our results revealed no conclusive evidence in favor of the notion that the concept of the Internet or internet access (via computers or smartphones) is automatically activated when participants are faced with hard trivia questions. We provide recommendations for follow-up research

1           **No conclusive evidence that difficult general**  
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3                           **A replication study**

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Guido Hesselmann<sup>1</sup>

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<sup>1</sup> Psychologische Hochschule Berlin (PHB), 10179 Berlin, Germany

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8

9 Corresponding author:

10 Guido Hesselmann

11 Am Köllnischen Park 2

12 10179 Berlin

13 Germany

14 Email: g.hesselmann@phb.de

## 15 **Abstract**

16 Access to the digital “all-knowing cloud” has become an integral part of our daily lives. It has been  
17 suggested that the increasing offloading of information and information processing services to the  
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23 situations where information is missing (e.g., because we might feel the urge to “google” the  
24 information). However, the “Google Stroop effect” could not be replicated in two recent replication  
25 attempts as part of a large replicability project. After the failed replication was published in 2018,  
26 the first author of the original study pointed out some problems with the design of the failed  
27 replication. In our study, we therefore aimed to replicate the “Google Stroop effect” with a research  
28 design closer to the original experiment. Our results revealed no conclusive evidence in favor of  
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30 automatically activated when participants are faced with hard trivia questions. We provide  
31 recommendations for follow-up research.

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## 34 **Introduction**

35 It seems intuitively plausible that today’s ubiquitous 24/7 access to the Internet via smartphones  
36 and computers will affect our cognitive functioning and strategies. Specifically, it has been  
37 suggested that different types of “cognitive offloading” (i.e., the use of our bodies, objects, and  
38 technology to alter the processing requirements of a task to reduce cognitive demand) may alter  
39 human cognition and metacognition in the short and long term (Risko & Gilbert, 2016). In the  
40 memory domain, one idea is that the Internet is taking the place not just of other humans as  
41 external sources of memory (“transactive memory”), but also of our own cognitive faculties (Ward,  
42 2013; Wegner & Ward, 2013). We increasingly offload information to “the cloud”, as almost all  
43 information today is readily available through a quick Internet search.

44 Evidence for such “Google effects on memory” has been presented in a much-cited<sup>1</sup> and  
45 influential<sup>2</sup> paper published in *Science* (Sparrow, Liu & Wegner, 2011). Across four experiments,  
46 the authors showed that a) when people expect to have future access to information, they have  
47 lower rates of recall of the information itself and enhanced recall instead for where to access it,  
48 and b) when faced with difficult general knowledge (or, trivia) questions, people are primed to  
49 think about the Internet and computers. The latter effect was demonstrated in one experiment  
50 (Exp.1) where participants answered easy or difficult trivia questions, and then completed a  
51 variant of the Stroop task (MacLeod, 1991). In a paradigm conceptually similar to the emotional  
52 Stroop paradigm (Algom, Chajut & Lev, 2004), participants responded to the ink color of written  
53 words, which were either related or unrelated to the Internet. Stroop-like interference from words  
54 relating to computers and Internet search engines was increased after participants answered  
55 difficult compared with easy questions, consistent with those terms being “primed” in participants’  
56 minds (Doyen et al., 2014). Briefly, the results seem to suggest that whenever information is  
57 needed and lacking, the concept of the Internet (including computer-related terms) is activated  
58 and can interfere with our behavior in subsequent tasks (e.g., because we might feel the urge to  
59 “google” the information).

60 In 2018, Camerer and colleagues published a meta-analysis of 21 replications of social science  
61 and psychology experiments published in *Science* or *Nature* between 2010 and 2015 (Camerer  
62 et al., 2018). This large replicability project included a replication of the “Google Stroop effect” by  
63 Sparrow and colleagues (2011). All materials and data from this replication – led by Holzmeister  
64 & Camerer - are freely available on OSF (<https://osf.io/wmgj9/>). In two separate experiments, the  
65 authors tested the hypothesis that, after answering a block of hard trivia questions, color-naming  
66 reaction times (RTs) are longer for computer-related terms than for general words. Neither  
67 experiment showed a significant effect despite adequate statistical power (see  
68 <https://osf.io/4rfme/> for a short summary of this replication). However, as the original authors of  
69 Sparrow et al. (2011) did not provide Holzmeister & Camerer with any materials or feedback on  
70 their inquiries, it was difficult to replicate the experimental design of the original study. After the  
71 replication had been completed and published, Sparrow noted some design differences compared  
72 to the original study (Sparrow, 2018). As Holzmeister & Camerer point out (Camerer et al., 2018),  
73 it cannot be ruled out that these design differences, including the manipulation of cognitive load

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<sup>1</sup> 1296 citations on Google Scholar, as of October 7 2020.

<sup>2</sup> The study is mentioned in a 2019 publication by the EU on harmful internet use:

<https://op.europa.eu/en/publication-detail/-/publication/fb2d58ea-8e58-11e9-9369-01aa75ed71a1/language-en/format-PDF/source-127484707>

74 (see below), influenced the replication result. Therefore, it was our aim to investigate the “Google  
75 Stroop effect” in a further study, based on the original experiment, the materials provided by  
76 Holzmeister & Camerer, as well as the critical comments by the original authors.

77

## 78 **Materials & Methods**

### 79 **Sample**

80 This work is based on an undergraduate student research project (“Experimentell-Empirisches  
81 Praktikum - ExPra”) at the Psychologische Hochschule Berlin (PHB). A total of 117 participants  
82 were tested. The sample consisted of students at the Psychologische Hochschule Berlin (PHB),  
83 as well as friends and families of the student experimenters (see acknowledgment). All  
84 participants provided written informed consent. The experiment was approved by the ethics  
85 committee of the PHB (approval number PHB10032019).

86

### 87 **Paradigm**

88 Our version of the experiment was based on two previous studies: Sparrow et al.’s original Exp.1  
89 (Sparrow, Liu & Wegner, 2011), and the replication study (Camerer et al., 2018). We incorporated  
90 comments provided by the first author of the original study (Sparrow, 2018), published in response  
91 to the failed replication<sup>3</sup>.

92 The original experiment tested the hypothesis that participants are primed to think about the  
93 Internet when faced with difficult trivia questions (e.g., “Did Benjamin Franklin give piano  
94 lessons?”). Participants first had to answer a block of either hard or simple question followed by  
95 a modified Stroop Task. In this task, Internet-related and neutral words were presented in random  
96 order, and participants were instructed to indicate the word’s color (blue or red) via button press.  
97 RTs to the words were measured as the dependent variable. In order to manipulate cognitive  
98 load, a random six-digit number was presented, and participants were instructed to memorize it  
99 for delayed retrieval (Figure 1). After their response in the modified Stroop Task, participants were  
100 asked to enter the six-digit number. The results from the modified Stroop task showed the  
101 predicted pattern: RTs to computer terms (e.g., Google) were longer than RTs to neutral terms

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<sup>3</sup> Our own request for further details about the experimental design remained unanswered (email from March 2019).

102 (e.g., Target), especially after participants were faced with difficult trivia questions (“question type  
103 x word type” interaction;  $F(1,66) = 5.02, p < .03$ ).

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*Figure 1 about here*

107 **Figure 1.** Schematic illustration of the modified Stroop paradigm. Participants first answer a list  
108 of 16 easy or hard trivia questions, followed by a block of color-naming trials (modified Stroop  
109 task). Before each Stroop block, or before each Stroop trial, a random six-digit number is  
110 presented for later retrieval (i.e., delayed retrieval at the end of a block of several Stroop trials, or  
111 at the end of each Stroop trial).

112

113 Although Sparrow et al. (2011) reported that they used eight target words related to computers  
114 and search engines, and 16 unrelated words, the total number of trials presented in each “hard  
115 question” and “easy question” block remained unclear, and also whether words were repeated.  
116 In their replication, Holzmeister & Camerer used the 24 words originally reported by Sparrow et  
117 al. (2011), and decided to run 48 trials per block, resulting in the repetition of words (i.e., each  
118 participant saw each word four times, twice in the “hard question” block, and twice in the “easy  
119 question” block.) In her response to the failed replication (Sparrow, 2018), Sparrow then strongly  
120 argues against the repetition of words, and reported the full set of 16 Internet-related words used  
121 in the original study.

122 The cognitive load manipulation is described as follows in the original study: “Participants are  
123 presented with words in either blue or red, and were asked to press a key corresponding with the  
124 correct color. At the same time, they were to hold a 6 digit number in memory, creating cognitive  
125 load” (Sparrow et al., 2011, supplement). In their replication, Holzmeister & Camerer decided to  
126 manipulate cognitive load by presenting a six-digit number before each Stroop task block. After  
127 the block (involving several trials), participants were asked to enter the memorized number. In her  
128 response, Sparrow strongly argues against this block-wise procedure and provided more detail  
129 about the original study: “[...] before each word, they were shown a different six digit number,  
130 which was reported back by them after each Stroop word”.

131 Finally, Sparrow mentions that the original experiment was run in 2006, which is why she believes  
132 that the computer terms used originally are obsolete and should not have been used in a

133 replication (Sparrow, 2018). In her response, she writes that she “would focus primarily on target  
134 words about phones (as they seem most ubiquitous), but would also be sure to pre-test many  
135 possible words to ensure their contextual relevance before putting them into the modified Stroop”.

136 For our replication study, we used the material provided by Holzmeister & Camerer on the open  
137 science platform OSF (<https://osf.io/wmgj9/>), and revised it according to Sparrow’s comments. All  
138 materials and data are available at OSF (<https://osf.io/cjgea/>). The experiment was implemented  
139 using oTree (Chen, Schonger & Wickens, 2016). We translated the trivia questions and Stroop  
140 words into the German language, and adjusted some questions to the German context (e.g., “Was  
141 Cat in the Hat written by J.D. Salinger?”). The experiment consisted of two blocks of 16 either  
142 hard or easy questions, followed by 24 Stroop words of which eight were Internet-related (e.g.,  
143 WLAN, Google, Website) and 16 were unrelated (e.g., frame, bottle, bamboo). The words were  
144 pre-tested for contextual relevance (see below), and randomly assigned to the easy and hard  
145 question condition. Words were presented in random order, and word color (blue or red) was  
146 randomly chosen on each trial. Participants were instructed to indicate the word color as quickly  
147 and as accurately as possible via button press (“e” for blue and “i” for red, using the index fingers  
148 of both hands). Participants were asked to place their fingers on the keys of the computer  
149 keyboard before the start of the Stroop task. Before the presentation of each Stroop word,  
150 participants had to memorize a random six-digit number for delayed retrieval after their response  
151 in the color-naming task.

152 After the main experiment, participants provided information about their age, level of education,  
153 color blindness, and what they thought the purpose of the experiment was. Finally, participants  
154 were asked what they would normally do when faced with a hard general knowledge question in  
155 their daily life: a) look up the answer on the Internet, b) ask someone who might know the answer,  
156 c) leave it at that. Including instructions, debriefing and signing the informed consent forms, the  
157 experiment lasted approximately 45 minutes in total.

158

## 159 **Word stimuli**

160 In the original study, the color naming task contained “8 target words related to computers and  
161 search engines (e.g., Google, Yahoo, screen, browser, modem, keys, Internet, computer), and  
162 16 unrelated words (e.g., Target, Nike, Coca Cola, Yoplait, table, telephone, book, hammer, nails,  
163 chair, piano, pencil, paper, eraser, laser, television)” (supplement, p.2). According to Sparrow  
164 (2018), the computer-related target words were selected from a larger set of the following 16

165 words: “Google, Yahoo, mouse, keys, Internet, browser, computer, screen, Altavista, Wikipedia,  
166 disk, Lycos, Netscape, modem, router, online” (p.1). The full list of words included in the set of  
167 general terms is not provided. Thus, at least in the case of computer terms, the number of target  
168 words used in the experiment was smaller than the number of available target words (eight and  
169 16, respectively). It remains unclear how the target words were chosen for each participant. What  
170 seems to be clear is that the words Target, Nike, Google, and Yahoo were chosen for each  
171 participant, because a within-subject comparison was calculated using this subset of words (see  
172 below). Furthermore, the authors of the original study write that the sets “were matched for  
173 frequency to the target words (11)” (supplement, p.2). Without the full word sets, this claim is hard  
174 to evaluate. A brief search in the referenced word corpus (reference 11) revealed no hit for the  
175 computer terms “Altavista” and “Google” (Nelson, McEvoy & Schreiber, 2004).

176 Based on Sparrow’s reply to the first replication (Sparrow, 2018), we prepared two new sets of  
177 German words, one set with general terms (32 words), and one set with computer terms (16  
178 words). As suggested by Sparrow (2018), we validated the contextual relevance of these words.  
179 31 naïve participants (mostly undergraduate students who did not participate in the main  
180 experiment) took part in an online survey (<https://www.surveymonkey.de/>). For each of the 48  
181 words, participants rated the contextual relevance (i.e., “Internet-relatedness”) on a 5-point scale  
182 (statement: “I think of the Internet when reading this word”; Rating: 1 = Strongly agree; 2 = Agree;  
183 3 = Neutral; 4 = Disagree; 5 = Strongly disagree). For computer words, the mean rating (i.e., the  
184 mean rating across the median ratings per participant) turned out to be 1.06, while it was 4.94 for  
185 the neutral terms.

186 Our list of computer (or, Internet-related) terms contained: website, data volume, email, search  
187 engine, Wikipedia, WLAN, app, Google, smartphone, hotspot, online, blog, Spotify, Firefox,  
188 Whatsapp, Chrome. The list of general (or, unrelated) terms contained words like nail or car, but  
189 also names of grocery stores (all words in German; full list on OSF). After completion of the study,  
190 we used the online DlexDB database to estimate word frequency in the two sets  
191 ([www.dlexdb.de/query/kern/typposlem/](http://www.dlexdb.de/query/kern/typposlem/)). The median absolute type frequency (corpus frequency)  
192 for the general terms was 374, while it was 23.5 for the computer terms. However, half of the  
193 words in the list of computer terms were not part of the data base (Wikipedia, WLAN, Google,  
194 smartphone, blog, Spotify, Firefox, Whatsapp). To what degree this difference in word frequency  
195 between the two sets could be problematic for the current experiment, is hard to say. Under the  
196 assumption that participants read the words when responding to their color, one would expect  
197 longer RTs for words in the set of computer terms due to the lower word frequency (Larsen,  
198 Mercer & Balota, 2006). The main effect of “word type” reported by Sparrow et al. (2011) could

199 parsimoniously be explained by differences in word frequency, if word sets were not matched.  
200 However, differences in word frequency between the two sets do not seem to preclude the  
201 proposed “question type x word type” interaction, which is driven by priming (according to the  
202 dual-route model). In a control analysis, we did not find evidence for an effect of word frequency  
203 on RTs in our data set<sup>4</sup>.

204 As Sparrow (2018) in her reply to the replication strongly argues against presenting each target  
205 word more than once (referring to “active thought suppression”), we decided to randomly select  
206 words for the easy and hard blocks. From our pool of 48 words, eight computer terms and 16  
207 general terms were presented in each block, so that each word was presented only once in the  
208 experiment. The words were randomly chosen for each participant. Of note, each word was  
209 presented twice in the original study, once in the easy block, and once in the hard block. Since  
210 we did not intend to select single words for post hoc pairwise tests, we did consider a strict “no  
211 word repetition” approach to be more in line with Sparrow’s (2018) suggestions. Table 1  
212 summarizes the known differences between the original study and the replication studies.

213

214

*Table 1 about here*

215

216 **Table 1.** Differences between the original study by Sparrow et al. (2011) and the replication studies. (\*)  
217 Original sample size is based on the supplementary information. (\*\*) Total number of trials is an informed  
218 guess based on the original study and the response to the failed replication (Sparrow, 2018).

219

## 220 **Data preprocessing**

221 We preregistered our analyses including confirmatory and exploratory statistical tests  
222 (<https://aspredicted.org/z3xt4.pdf>), and later decided to restrict the analysis to confirmatory tests.  
223 All data are available on OSF (<https://osf.io/cjgea/>). Data were preprocessed and analyzed using  
224 R version 3.3.2 ([www.r-project.org](http://www.r-project.org)), and RStudio version 1.0.136 ([www.rstudio.com](http://www.rstudio.com)). The original  
225 “csv” data files were exported from oTree, imported into R, converted into the long format and  
226 merged using custom R scripts. Each student experimenter contributed one “csv” file containing  
227 the data from multiple participants. The resulting data file in the long format thus contains blocks

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<sup>4</sup> Using a Bayes Factor approach (<https://richarddmoney.github.io/BayesFactor/>), we found that a model not containing word frequency as predictor was preferred to a model containing word frequency by a factor of 16. Details can be found in the R analysis script on OSF.

228 of data from different student experimenters, because we did not sort the data according to  
229 recording time and date.

230 The age distribution of participants turned out to be heavily skewed (mean age: 31 years; range:  
231 18 – 73). This was because the participant sample included students' families and friends, and  
232 we originally did not set a maximum age. Since the sample in the original paper (Sparrow, Liu &  
233 Wegner, 2011) consisted of undergraduate students (supplement, p.2), we decided to deviate  
234 from our preregistered protocol, and set the maximum age as the 75% quantile of the age  
235 distribution (44 years). In the remaining sample of 89 participants, the mean age was 24 years.

236 A second deviation from the preregistered protocol was due to the fact that we originally assumed  
237 that trials with incorrect responses (i.e., when participants pressed the key for the wrong color)  
238 should be excluded from the analysis. According to the replication report (<https://osf.io/84fyw/>),  
239 which includes personal communication with the original authors, this was not the case in the  
240 original study. We therefore included trials with correct and incorrect responses in the color-  
241 naming task. (Note that trials with incorrect responses in the memory task were not excluded,  
242 either.)

243 Although not specified in the original study, and neither in the replication study, we preregistered  
244 an additional exclusion of trials with RT outliers and anticipatory responses ( $< 0.1s$ ). We defined  
245 RT outliers using the interquartile range (IQR) method (Tukey, 1977), separately for each  
246 participant. These criteria resulted in the exclusion of  $7 \pm 3\%$  of trials (mean percentage  $\pm$  standard  
247 deviation). For our final analysis, we did not exclude RT outliers, but also report the results of the  
248 analysis including the exclusion of RT outliers.

249

## 250 **Data analysis**

251 For each participant, we calculated the performance in the easy and hard questionnaires, the  
252 performance in the number memory task, and the mean RT in each of the four conditions. The  
253 condition averages from all participants were then exported into JASP 0.10.2 ([https://jasp-](https://jasp-stats.org/)  
254 [stats.org/](https://jasp-stats.org/)) for frequentist and Bayes Factor (BF) analysis, using default Cauchy priors (scale  
255 0.707). To test the predicted “question type x word type” interaction, we calculated the following  
256 difference and tested it against zero using a two-sided paired test:  $[RT(\text{computer}) -$   
257  $RT(\text{general})]_{\text{hard}} - [RT(\text{computer}) - RT(\text{general})]_{\text{easy}}$ . Performance in the number memory task was  
258 calculated for all trials (i.e., including trials with RT outliers in the color-naming task).

259

260 **Results**

261 Participants found the easy questions to be answerable ( $97 \pm 4\%$ , mean accuracy  $\pm$  standard  
262 deviation), but had difficulty finding the correct answers to the hard questions ( $60 \pm 11\%$ ). As in  
263 the original study (98% versus 47%), this difference was significant ( $t_{88} = 48.31$ ,  $p < .001$ ). Mean  
264 accuracies in the color-naming task and number memory task were high ( $98 \pm 3\%$  and  $81 \pm 16\%$ ,  
265 respectively).

266 Figure 2A plots the RT data from the color-naming task. The dual-route model predicts that  
267 computer terms create more interference, and thus are associated with longer RTs than general  
268 terms, in particular in hard question blocks. The results show that in easy question blocks, mean  
269 RT was  $830 \pm 366$  ms for general terms, and  $901 \pm 620$  ms for computer terms (mean  $\pm$  standard  
270 deviation). In hard question blocks, mean RT was  $825 \pm 453$  ms for general terms, and  $821 \pm$   
271  $379$  ms for computer terms. Thus, the RT data do not show the predicted pattern. Accordingly,  
272 the sequential Bayes Factor (BF) analysis yielded a final  $BF_{01}$  of 5.07 in favor of the null over the  
273 alternative hypothesis, after the data from  $N=89$  participants were taken into account (Figure 2B).  
274 The observed data are thus 5 times more likely under the null model than under the alternative  
275 model (i.e., the “question type x word type” interaction). When the specific data pattern reported  
276 in the original study was considered as alternative model in an exploratory analysis, our data were  
277 16 times more likely under the null model ( $BF_{0+} = 16.43$ ). The preregistered two-sided one-sample  
278 t-test was not significant ( $t_{88} = -1.04$ ,  $p = .301$ ).

279 The pattern of results remained the same when incorrect responses in the color-naming task were  
280 excluded. When RT outliers were excluded from data analysis, overall mean RTs decreased, but  
281 the predicted interaction could still not be observed ( $BF_{01} = 3.74$ ;  $t_{88} = 1.31$ ,  $p = .194$ ). In easy  
282 question blocks, mean RT was  $737 \pm 296$ ms for general terms, and  $723 \pm 295$ ms for computer  
283 terms (mean  $\pm$  standard deviation). In hard question blocks, mean RT was  $707 \pm 268$ ms for  
284 general terms, and  $712 \pm 261$ ms for computer terms (data not plotted in a figure).

285 In the debriefing after the main experiment, 11 out of 89 participants did not provide a response  
286 (e.g., closed the browser before answering). 73% (57/78) of all responders said that they would  
287 look up the answer on the Internet when faced with a hard general knowledge question in their  
288 daily life; 18% (14/78) said that they would ask someone who might know the answer, and 9%  
289 (7/78) responded that they would “leave it at that”. When we restricted the RT data analysis to  
290 participants consulting the Internet ( $N=57$ ), the pattern of results was very similar to the one

291 reported above ( $BF_{01} = 5.01$ ). Finally, when all participants ( $N=117$ ) were included in the data  
292 analysis, the pattern of results turned out to be 9 times more likely under the null model than under  
293 the alternative model ( $BF_{01} = 9.31$ ).

294

295

*Figure 2 about here*

296

297 **Figure 2.** Main results ( $N=89$ ). (A) Reaction time (RT) data from the color-naming task. Grey  
298 squares represent the mean RT in the “easy question” blocks, white squares represent the mean  
299 RT in the “hard question” blocks. Errors bars represent the standard error of the mean. (B)  
300 Sequential Bayes Factor (BF) analysis of the “question type x word type” interaction. User prior  
301 refers to a Cauchy prior with scale 0.707, wide prior to a Cauchy prior with scale 1, and ultrawide  
302 prior to a Cauchy prior with scale  $\sqrt{2}$ .

303

#### 304 **Statistical issues in the original study**

305 During our work on this project, we noticed three statistical issues in the original paper by Sparrow  
306 et al. (2011). In the following paragraph, we address these observations in turn.

307 First, it remains unclear whether  $N=69$  or  $N=46$  participants were tested in Experiment 1 of the  
308 original paper (Sparrow, Liu & Wegner, 2011). In the supporting online material<sup>5</sup>, the authors write  
309 that “Forty-six undergraduate students (28 female, 18 male) at Harvard University were tested in  
310 a within subjects experiment” (p.2). In their 2x2 within-subject design (easy/hard questions;  
311 computer/general words), the correct degrees of freedom (df) would then be 45 for paired t-tests,  
312 as well as for main effects, the interaction and simple main effects in the rm-ANOVA. Under the  
313 assumption that  $N=69$  participants were tested, the correct df would be 68. In the main text and  
314 supplement of the original paper, the reported df is 68 for paired t-tests, and 66 for the rm-ANOVA.  
315 According to the authors of the replication, the original authors initially confirmed that the sample  
316 size was 46 participants, and that dfs were misreported in the paper, but after the publication of  
317 the replication the original authors pointed out that the number of participants was 69

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<sup>5</sup> <https://science.sciencemag.org/content/suppl/2011/07/13/science.1207745.DC1>

318 (<https://osf.io/84fyw/>). While the reported t-, F-, and p-values appear to be in better agreement  
319 with the N=69 scenario<sup>6</sup>, the reported dfs are incorrect in both scenarios.

320 Second, two computer-related words (Google/Yahoo), and two unrelated words (Target/Nike)  
321 were selected for analysis in the original paper. In the main text, RT data are reported only for  
322 this subset, together with the “question type x word type” interaction ( $F(1,66) = 5.02, p < .03$ ). The  
323 reasoning behind this post hoc selection (i.e., selection of four words out of a pool of Stroop  
324 words) remains unclear. Without further information, it remains possible that the choice was made  
325 after seeing the data. Such post hoc choices and data-contingent analyses are misleading when  
326 they are not presented as exploratory analysis. The potential impact of this post hoc selection  
327 should not be underestimated. As pointed out by Sparrow in a reply to the failed replication, “each  
328 Stroop word was seen only once by participants” (Sparrow, 2018). Hence, the RTs for  
329 Google/Yahoo and Target/Nike reported in the original paper are based on single trials per  
330 participant. Given such noisy measurements with low precision (Smith & Little, 2018), the authors  
331 might have capitalized on chance by selecting a subset of words for their main analysis.

332 Third, two paired t-tests on word type are reported for the complete data set (“hard questions”  
333 condition, computer words versus general words:  $t(68) = 3.26, p < .003$ ; “easy questions”  
334 condition,  $t(68) = 2.98, p < .005$ ). The “question type x word type” interaction is reported only for  
335 the 4-word-subset ( $F(1,66) = 5.02, p < .03$ ). Based on visual inspection of the reported average  
336 RTs, it seems plausible that the “question type x word type” interaction should be smaller for the  
337 complete data set (Figure 3A) than for the 4-word-subset (Figure 3B). Sparrow et al. (2011) report  
338 the following result in the supplement: “Taking out the 4 terms (Google/Yahoo and Target/Nike)  
339 which yielded an interaction with easy/hard questions ( $F(1,66) = 5.52$  [sic],  $p < .03$ ), the interaction  
340 between computer and general terms and easy/hard questions *remains* significant  $F(1,66) = 9.49,$   
341  $p < .004$ ” (p.3, italics added). In fact, the interaction for the reduced data set (i.e., all data minus  
342 the 4-word-subset) turned out to be *larger* than the interaction reported for the subset (F-values  
343 9.49 and 5.52, respectively). This result seems difficult to reconcile with the reported data, but  
344 access to the original data would be necessary to clarify this point.

345

346

*Figure 3 about here*

347

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<sup>6</sup> In the main text of Sparrow et al. (2011), the simple effect is reported as follows:  $F(1,66) = 4.44, p < .04$  (exact p-value: .03891. For N=46, the result would be:  $F(1,45) = 4.44, p = .040712$ , and thus  $p > .04$ ).

348 **Figure 3.** Reaction time (RT) data from Exp.1 in Sparrow et al. (2011). A) RTs for the complete  
349 data set (16 general words, 8 computer-related words). B) RTs for the 4-word-subset (2 general  
350 words: Target and Nike; 2 computer-related words: Google and Yahoo). Grey squares represent  
351 the mean RT in the “easy question” condition, white squares represent the mean RT in the “hard  
352 question” condition. Errors bars represent the standard error of the mean (for N=69).

353

## 354 **Discussion**

355 Although the majority of participants in our study reported that they would normally look up the  
356 answer to hard general knowledge questions on the Internet, we did not find evidence for the  
357 “Google Stroop effect”, as originally published by Sparrow et al. (2011). Thus, our data are more  
358 in line with the results from Camerer et al. (2018) who failed to replicate the original effect in two  
359 independent experiments. Importantly, the design of our study considered the suggestions for  
360 improvement provided by Sparrow (2018) in response to the failed replications. Based on her  
361 commentary, we carefully updated and validated the computer-related terms, strictly avoided  
362 word repetitions, and manipulated cognitive load as in the original study.

363 It seems worthwhile to take a closer look at the hypothetical cognitive model underlying the  
364 “Google Stroop effect”. Sparrow et al. (2011) describe their Exp.1 as a modified Stroop task, as  
365 follows: “People who have been disposed to think about a certain topic typically show slowed  
366 reaction times (RTs) for naming the color of the word when the word itself is of interest and is  
367 more accessible, because the word captures attention and interferes with the fastest possible  
368 color naming” (p.776). Classic and modified Stroop tasks, such as the emotional Stroop task,  
369 have been discussed in much detail elsewhere (MacLeod, 1991; Algom, Chajut & Lev, 2004). In  
370 Exp.1 by Sparrow et al. (2011), there are two colors (red, blue), and two types of words: general  
371 terms (e.g., sport) and computer terms (e.g., Google). The authors propose a priming mechanism  
372 that specifically affects response times in trials with computer terms: “not knowing the answer to  
373 general knowledge questions primes the need to search for the answer, and subsequently  
374 computer interference is particularly acute” (p.776).

375 According to this model, computer terms become more accessible when the concept of  
376 knowledge is activated, or when information necessary for answering a trivia question is lacking,  
377 which results in more interference. We think that at least two points need to be made about this  
378 model. First, what remains unspecified is the duration of the proposed priming effect (i.e., for how  
379 long the computer terms are more accessible than general terms due following the activation of  
380 concepts). Follow-up studies could focus more on the temporal dynamics of the proposed priming

381 effect. Perceptual and semantic priming effects are typically short-lasting, within the range of  
382 hundreds of milliseconds, while priming effects from social psychology (e.g., the “Florida effect”)  
383 are substantially longer lasting, but have turned out to be not robust (Harris et al., 2013; Doyen et  
384 al., 2014). Second, the exact role of cognitive load (i.e., working memory load) for the “Google  
385 Stroop effect” remains somewhat unclear. In her response to the failed replications, Sparrow  
386 (2018) links the working memory task to the paradigm of active thought suppression: “when  
387 people are asked explicitly not to think about a single target word, they must engage in active  
388 suppression” (p.1). Sparrow (2018) cites an earlier study (Wegner & Erber, 1992) in which  
389 participants performed a color-naming task similar to Exp.1 from Sparrow et al. (2011). In this  
390 experiment, strongest Stroop-like interference was observed when participants were suppressing  
391 a specific target word under cognitive load, and when they were asked to name the color of this  
392 target word. In contrast to the “Google Stroop effect”, however, participants were asked to actively  
393 suppress a single word, so that the importance of high cognitive load in one task might not tell us  
394 much about the role of high cognitive load in the other task. Alternatively, it could be argued the  
395 word’s meaning (in contrast to its color) acts as distracting information in the color-naming task,  
396 and that high working memory load increases distractor processing (Lavie, 2005). Therefore, the  
397 manipulation of cognitive load might be crucial for the processing along the word reading pathway,  
398 and thus for the emergence of the “Google Stroop effect”.

399 Our data, however, do not support the notion that the concept of the Internet (together with  
400 computer-related terms) becomes automatically activated when participants need to answer  
401 difficult general knowledge questions. We are aware that our study does not provide a definite  
402 answer, and the potential effects of “cognitive offloading” on human cognition (Risko & Gilbert,  
403 2016) are definitely worth further attention and investigation. As mentioned above, the original  
404 study by Sparrow et al. (2011) avoided word repetitions, so that the RT data from each participant  
405 were based on single presentations of target words. Given such noisy RT measurements, in  
406 combination with the suboptimal analysis of variance on the sample mean (Whelan, 2008), post  
407 hoc selection of target words can easily lead to the wrong impression that an effect exists (e.g.,  
408 we might find a “Wikipedia Stroop effect” or “Firefox Stroop effect” in our data set). Therefore, we  
409 recommend using the complete data set in future studies when testing for the crucial “question  
410 type x word type” interaction, preferably with linear mixed-effects models that can better account  
411 for stimulus-driven variability in RTs than repeated measures ANOVA (Baayen, Davidson &  
412 Bates, 2008). Fitting more complex linear models, e.g., models with random slopes, would also  
413 require more data than in the present experimental design in which a limited set of words is  
414 presented only once per participant (Meteyard & Davies, 2020).

415

## 416 **Conclusion**

417 Our results revealed no evidence in favor of the notion that the concept of the Internet or internet  
418 access (via computers or smartphones) becomes automatically activated whenever participants  
419 are faced with hard trivia questions. Thus, the “Google Stroop effect” might be much smaller than  
420 previously thought, and less robust to variations in the experimental design. What else have we  
421 learned from this second replication of the “Google Stroop effect”? Our work on this project  
422 revealed that the original research design might not be a good starting point to further investigate  
423 this effect. To study the effects of the digital “all-knowing cloud” on our cognition, research designs  
424 with more precision and power are clearly necessary. Finally, as has been so adequately pointed  
425 out by Holzmeister & Camerer, this set of replications “illustrates the importance of open access  
426 to all of the materials of published studies for conducting direct replications and accumulating  
427 scientific knowledge” (Camerer et al., 2018).

428

429

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441

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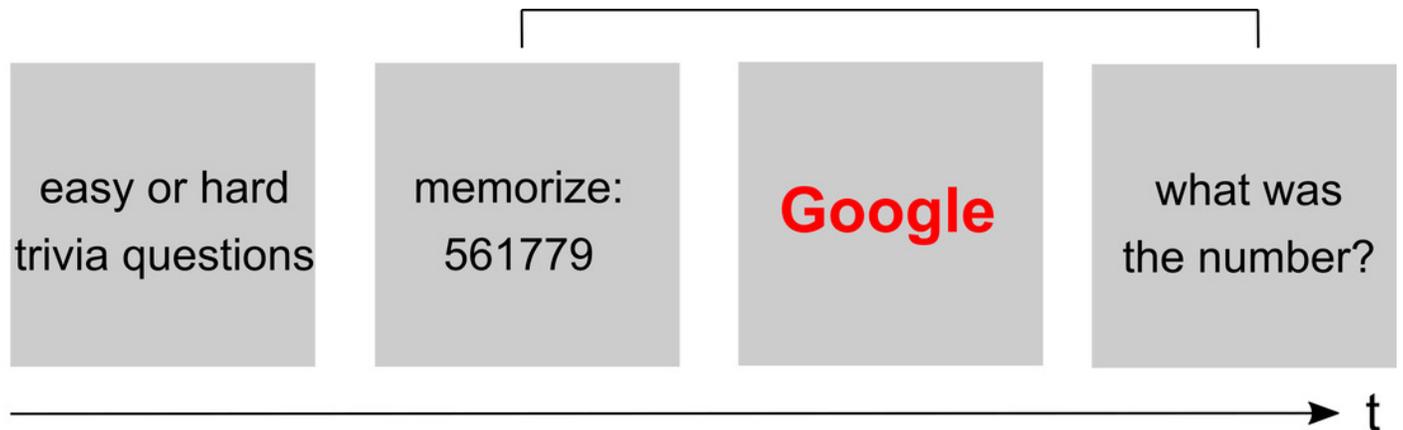
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495

## Figure 1

Schematic illustration of the modified Stroop paradigm.

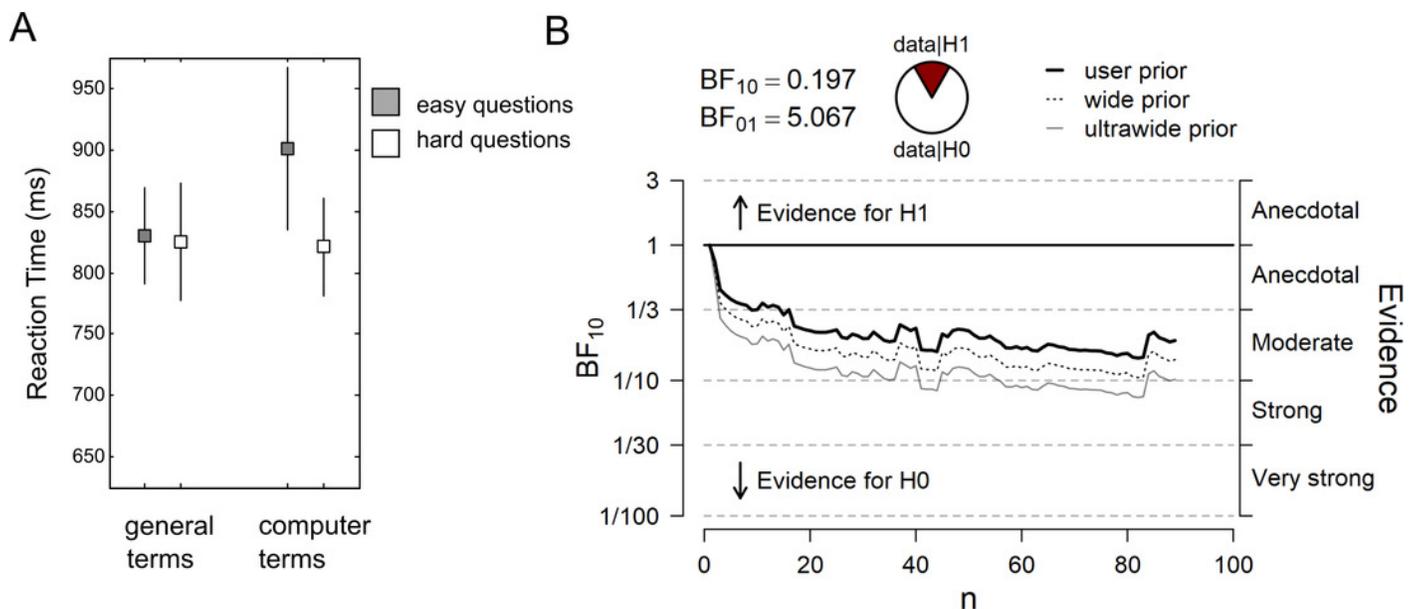
Participants first answer a list of 16 easy or hard trivia questions, followed by a block of color-naming trials (modified Stroop task). Before each Stroop block, or before each Stroop trial, a random six-digit number is presented for later retrieval (i.e., delayed retrieval at the end of a block of several Stroop trials, or at the end of each Stroop trial).



## Figure 2

Main results (N=89)

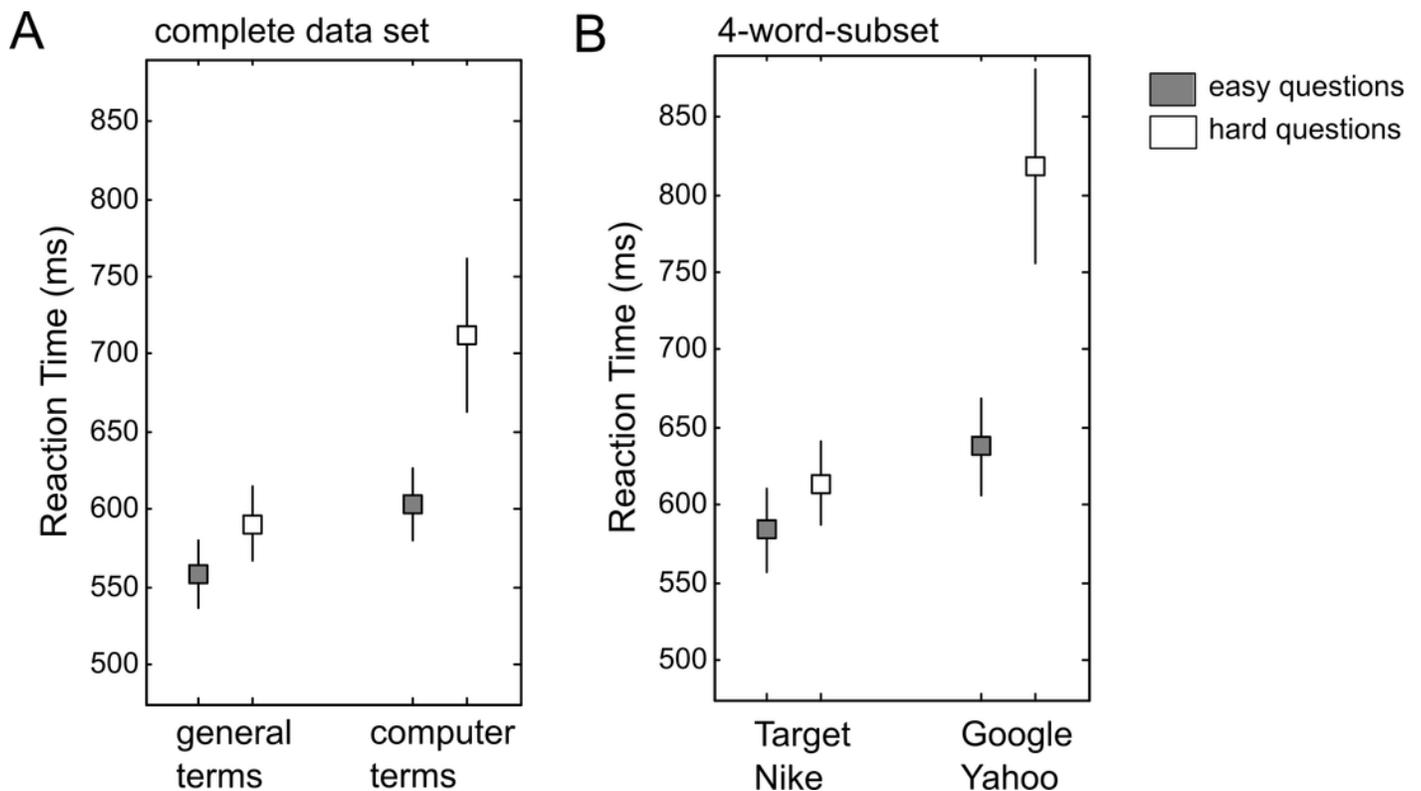
(A) Reaction time (RT) data from the color-naming task. Grey squares represent the mean RT in the “easy question” blocks, white squares represent the mean RT in the “hard question” blocks. Errors bars represent the standard error of the mean. (B) Sequential Bayes Factor (BF) analysis of the “question type x word type” interaction. User prior refers to a Cauchy prior with scale 0.707, wide prior to a Cauchy prior with scale 1, and ultrawide prior to a Cauchy prior with scale  $\sqrt{2}$ .



## Figure 3

Reaction time (RT) data from Exp.1 in Sparrow et al. (2011)

A) RTs for the complete data set (16 general words, 8 computer-related words). B) RTs for the 4-word-subset (2 general words: Target and Nike; 2 computer-related words: Google and Yahoo). Grey squares represent the mean RT in the “easy question” condition, white squares represent the mean RT in the “hard question” condition. Errors bars represent the standard error of the mean (for N=69).



**Table 1** (on next page)

## Table 1

Differences between the original study by Sparrow et al. (2011) and the replication studies.

(\*) Original sample size is based on the supplementary information. (\*\*) Total number of trials is an informed guess based on the original study and the response to the failed replication (Sparrow, 2018).

- 1 **Table 1.** Differences between the original study by Sparrow et al. (2011) and the replication studies. (\*)
- 2 Original sample size is based on the supplementary information. (\*\*) Total number of trials is an informed
- 3 guess based on the original study and the response to the failed replication (Sparrow, 2018).

4

	Sparrow et al. (2011), Exp.1	Camerer et al. (2018)	Hesselmann (2020)
Data collection	2006	2017	2019
Presentation software	DirectRT	oTree	oTree
Participant sample	Undergraduate students (USA)	Students and non- students (USA)	Students and non- students (Germany)
Sample size	N=46*	N=104 & N=130	N=117
Trivia questions	Original set (16 easy, 16 hard)	Original set (16 easy, 16 hard)	Revised & translated set (16 easy, 16 hard)
Stroop words	Original set (incl. 16 internet words)	Original subset (incl. 8 internet words)	Revised, translated & validated set (incl. 16 internet words)
Number memory task	On each Stroop trial	1x per block of trials (easy/hard)	On each Stroop trial
Number of presentations per Stroop word	1x per block of trials (easy/hard)**	2x per block of trials (easy/hard)	1x per experiment
Total number of trials	48 (24 easy, 24 hard)**	96 (48 easy, 48 hard)	48 (24 easy, 24 hard)
Participant debriefing	Unknown	Unknown	Yes

5