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1 **The seductive allure of technical language and its effect on covid-**
2 **19 vaccine beliefs and intentions**

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17 We thank Dr. Ian L. Jones for his expert advice in constructing the vaccine explanations.
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34 **Abstract**

35 Previous research has demonstrated a ‘seductive allure’ of technical or reductive
36 language such that bad (e.g., circular) explanations are judged better when irrelevant
37 technical terms are included. We aimed to explore if such an effect was observable in
38 relation to a covid-19 vaccinations and if this subsequently affected behavioural
39 intentions to take up a covid-19 vaccine. Using a between subjects design we
40 presented participants (N=996) with one of four possible types of vignette that
41 explained how covid-19 vaccination and herd immunity works. The explanations varied
42 along two factors: (1) Quality, explanations were either good or bad (i.e., tautological);
43 (2) Language, explanations either contained unnecessary technical language or did
44 not. We measured participants’ evaluation of the explanations and intentions to
45 vaccinate. We demonstrate a ‘seductive allure’ effect of technical language on bad
46 vaccine explanations. However, an opposite ‘repellent disdain’ effect occurred for good
47 explanations which were rated worse when they contained technical language.
48 Moreover, we show that evaluations of explanations influence intentions to vaccinate.
49 We suggest that misinformation that includes technical language could be more
50 detrimental to vaccination rates. Importantly, however, clear explanatory public health
51 information that omits technical language will be more effective in increasing intentions
52 to vaccinate.

53

54 **Introduction**

55

56 Thanks to monumental and historic efforts, multiple covid-19 vaccinations have now been
57 approved for use in numerous countries and have been shown to be safe and effective [1–3].
58 These vaccinations are at the heart of the global effort to mitigate the ongoing pandemic. As

59 such, public health interventions and campaigns are focused on increasing public
60 understanding of, and promoting behavioural intentions towards, vaccination.

61

62 Voluntary uptake of the vaccine is one of the most pressing issues facing efforts to control the
63 pandemic. Without a sizeable proportion of the population agreeing to be vaccinated, efforts to
64 minimise the serious effects of the coronavirus disease, or even possibly eliminate it, will be
65 hampered. Even before the current pandemic, the WHO listed vaccine hesitancy as one of the
66 top ten threats to global health [4]. Refusal to take up routine vaccinations has been linked to a
67 rise in vaccine preventable diseases, not just in those who refuse the vaccine themselves but
68 also in the broader population [5]. Initial global concerns about high rates of hesitancy towards
69 a covid-19 vaccine [6-7] have been somewhat ameliorated by high acceptance of the vaccine
70 in the presence of vaccine availability [8]. Although vaccine hesitancy rates fluctuate [9] they
71 are clearly not negligible – efforts to curtail the negative consequences of the pandemic rely
72 heavily on a successful global vaccination project.

73

74 Public health interventions depend on public engagement which in turn requires effective
75 dissemination of information and communication to persuade and co-ordinate a public
76 response. Sometimes confounding this goal, the ubiquity of social media has been linked to the
77 spread and prevalence of *misinformation*, directly impacting public health measures [10].
78 Loomba et al. [14] exposed participants to either information or to misinformation about a
79 potential covid-19 vaccine and asked participants to rate their intent to vaccinate.
80 Misinformation induced a reduction in the number of participants who said they would
81 “definitely” take a covid-19 vaccine, whereas those who were exposed to factual information
82 showed no such reduction. Loomba et al. [14] also report evidence that misinformation
83 purporting to be based in science has a particularly damaging effect on vaccination intentions.

84

85 Misinformation can be subtle; it may for example include ‘misleading content’ that, while not
86 necessarily explicitly false or incorrect, significantly reformulates or re-contextualises selected
87 details [12]. Further, whilst the spread of misinformation is undoubtably detrimental to public
88 health interventions, the way in which veridical information is communicated is also of critical
89 concern and requires empirical investigation. Given that knowledge of vaccines is substantially
90 correlated with willingness to vaccinate [13] there is a clear rationale for determining effective
91 ways to communicate vaccine knowledge.

92

93 For the current research we borrowed an idea that has explored how people engage with
94 explanatory scientific information and specifically whether reductive or technical language
95 obfuscates understanding; commonly referred to as ‘seductive allure’. Initially reported in the
96 field of psychology and neuroscience, the ‘seductive allure’ effect results in an increase in
97 participant’s rating of an explanation when irrelevant neuroscientific terms are included [14].
98 Subsequently research by Hopkins and colleagues [18] demonstrated that the seductive allure
99 phenomenon is observable for explanatory texts across an array of disciplines and argued that
100 the allure is due to a general preference for reductive information. That is to say, explanatory
101 information about a broad range of topics is ‘seductive’ when unnecessary reductive language
102 is included – i.e. explanations that make reference to more fundamental processes or smaller
103 components but, nevertheless, omit any explanatory information [15]. Whilst reductive or
104 technical language is often useful, its mere presence isn’t necessarily so, especially when it
105 provides no further causal information about the phenomena to be explained. Very little
106 research has explored whether the inclusion of unnecessary technical terminology has any
107 effect on behavioural intentions [but see 16] and this has yet to be explored in the context of
108 health behaviours.

109

110 Although ‘bad’ (i.e., tautological) explanations are reliably judged better by the addition of
111 technical or reductive information [14,15], the effect of technical language on explanations that
112 are ‘good’ (i.e., contain explanatory – not tautological – information) is less clear. Weisberg
113 et al. [17] found that, among domain experts, good explanations were judged *worse* by the
114 inclusion of technical language but this inversion of the seductive allure effect is less clear in
115 students, the lay population and in subjects other than neuroscience [14,15,17]. It remains an
116 open question as to how both good and bad explanations, with and without technical language,
117 may influence opinions about vaccinations and behavioural intentions during a global
118 pandemic. Some insight can be gained from previous research that has looked at using technical
119 terms such as “influenza vaccination” compared to more colloquial terms like “flu shot” and
120 measuring vaccination intentions [16]. These findings show that behavioural intentions to
121 vaccinate increase when technical language is used. However, these findings don’t address this
122 interacts with the quality of the explanation and were not explored during the current global
123 pandemic.

124

125 In the current study, participants were presented with information about a covid-19 vaccine.
126 We varied the information by manipulating two factors: how good/bad and how technical/non-
127 technical the explanations were. ‘Good’ explanations provided a mechanistic account as to how
128 vaccines and herd immunity works (such as: Vaccines work by triggering an immune response
129 within the body). ‘Bad’ explanations were circular in nature and provided no underlying
130 explanation (such as: Vaccines work because when you are immunized you have the vaccine
131 in your body). ‘Technical’ explanations included technical language irrelevant to the
132 explanation but related to vaccinations and covid-19 (such as reference to “pathogens such as
133 viruses” rather than merely “viruses”). After reading the information we asked participants to

134 rate the explanation they saw in terms of how ‘satisfying’ and how ‘good’ the explanation was
135 (as in [14]) and whether reading the information affected their intention to take a covid-19
136 vaccine. Finally, we measured vaccine hesitancy dispositions [18]. Exploring how good quality
137 explanations are affected by the addition of technical language provides insight into public
138 health communication. Specifically, we are able to consider whether good explanations should
139 include technical language in descriptions of vaccinations, whether necessary or not, to
140 promote engagement with vaccination programmes. Further, by considering responses to low
141 quality explanations, with and without technical language, we can examine how poorer
142 explanations, such as misinformation, or simply badly communicated information, affects
143 beliefs and behavioural intentions towards vaccines.

144

145

146 We expected to replicate previous ‘seductive allure’ findings and show that descriptions of
147 immunity and vaccination will be rated more positively when they include unnecessary
148 technical information. In line with previous findings among non-expert populations (i.e., those
149 with no specific degree of skill or knowledge in a given subject), we expected this effect to be
150 strongest for bad explanations. Moreover, if technical information also has a ‘seductive’ effect
151 on behavioural intentions then we would expect those exposed to bad explanations with
152 irrelevant scientific terms to be more likely to intend to take up a covid-19 vaccine compared
153 to those who read bad explanations without technical language. Finally, we also hypothesised
154 that, compared to bad explanations, good explanation would increase the intention to vaccinate.

155

156

157 **Methods**

158

159 Participants

160

161 We conducted an online survey of 1003 adults in the United Kingdom (UK) recruited using
162 Prolific Academic. Data was recorded using Qualtrics. Respondents were paid £0.75 for their
163 time. The survey was conducted on December 16th 2020, which was approximately two weeks
164 after the Medicines and Healthcare Products regulatory Agency (MHRA) in the UK formally
165 approved the use of the covid-19 vaccine developed by Pfizer and BioNTech. We removed
166 participants who identified as having had the covid-19 vaccine (n=7) from any further analysis;
167 only those who were unvaccinated were included in the analysis. This resulted in a total of 996
168 participants. Each participant was randomly allocated to one of four different categories of the
169 statement about vaccinations that was either good or bad and either contained technical
170 language or did not: good technical (n=247), good non-technical (n=249), bad technical
171 (n=249) or bad non-technical (n=251) (see Table 1). The study was approved by the Middlesex
172 University Research Ethics Committee.

173

174

175

176

177

	Good		Bad		Total
	Technical	Non-technical	Technical	Non-technical	
N	247	249	249	251	996
Mean age (SD)	37.47 (13.30)	35.63 (13.30)	36.59 (13.05)	36.65 (13.15)	36.58 (13.19)
Gender N (%)					
Female	151 (61.1)	156 (62.7)	152 (61.0)	159 (63.3)	618 (62)
Male	96 (38.9)	93 (37.3)	97 (39.0)	92 (36.7)	378 (38)
Education N (%)					
No university degree					
No formal qualifications	1 (0.4)	3 (1.2)	1 (0.4)	3 (1.2)	8 (0.8)
Secondary education	24 (9.7)	17 (6.8)	24 (9.6)	24 (9.6)	89 (8.9)
High school diploma/A-levels	68 (27.5)	55 (22.1)	54 (21.7)	45 (17.9)	222 (22.3)
Technical/community college	20 (8.1)	23 (9.2)	22 (8.8)	23 (9.2)	88 (8.8)

University degree					
Undergraduate degree	91 (36.8)	101 (40.6)	108 (43.4)	98 (39.0)	398 (40)
Graduate degree	35 (14.2)	42 (16.9)	35 (14.1)	46 (18.3)	158 (15.9)
Doctorate degree	8 (3.2)	8 (3.2)	5 (2.0)	12 (4.8)	33 (3.3)
Employment N (%)					
Employed					
Full-Time	122 (49.4)	133 (53.4)	129 (51.8)	128 (51)	512 (51.4)
Part-Time	47 (19.0)	46 (18.5)	57 (22.9)	62 (24.7)	212 (21.3)
Unemployed					
Not in paid work	40 (16.2)	36 (14.5)	41 (16.5)	33 (13.1)	150 (15.1)
Unemployed	38 (15.4)	34 (13.7)	22 (8.8)	28 (11.2)	122 (12.2)
Politics N (%)					
Centre	123 (49.8)	97 (39.0)	97 (39.0)	101 (40.2)	418 (42)
Left	97 (39.3)	124 (49.8)	112 (45.0)	119 (47.4)	452 (45.4)
Right	27 (10.9)	28 (11.2)	39 (15.7)	31 (12.4)	125 (12.6)
N/A	0 (0)	0 (0)	1 (0.4)	0 (0)	1 (0.1)

178 **Table 1.** Socio-demographic information for participants as a function of group, and the total.

179 Design and Procedure

180

181 Participants were presented with a short explanation about how vaccination, immunisation and
182 herd immunity work. The explanation was either good or bad and either contained technical
183 language or did not, forming four possible categories of which one was presented to any one
184 participant. To minimise the possibility of spurious idiosyncratic effects arising from the
185 wording of the explanations - other than the intended manipulations - two versions of each of
186 the four categories of explanations were created and randomly allocated to participants. The
187 versions of the explanations varied on the same two dimensions (good/bad and technical/non-
188 technical) but differed in the precise language used. An example of the statements for each
189 category from one version is presented in Table 2. All of the statements and questionnaire
190 questions are available online on Open Science Framework (osf; <https://osf.io/wq849/>). The
191 good explanations were originally sourced from four reputable websites (nhs.uk, who.int,
192 immunology.org, cdc.gov) and further modified to fit the current study.

193

194 After reading the explanation participants were first asked to answer Question 1: “After reading
195 this explanation would you be more or less likely to take a COVID-19 vaccine”, responses
196 were given on a 7-point scale from very unlikely to very likely, with the middle point indicating

197 no change. We took no measure of vaccination intentions before participants are presented with
198 an explanation, and therefore don't directly measure a change in intentions. However, because
199 we do ask participants to report on a relative change based on their reading of the explanation,
200 we have conceptualised this as a change in intentions. After participants committed an answer
201 to this question two further questions became visible and they were unable to change their
202 response to Question 1. Questions 2 and 3 asked participants to judge how good or satisfying
203 the explanation was, respectively, on a 7-point scale. These two questions were the same as
204 those asked of participants in the original 'seductive allure' paper [14]. After answering these
205 questions participants were asked to ignore the information presented in the explanation and
206 complete the Vaccine Hesitancy Scale (VHS;[18]). The VHS is a ten-item scale aimed at asking
207 parents about their views on childhood vaccines; we reworded the scale to refer to adult
208 vaccination to make it more appropriate for the survey respondents. The reworded scale was
209 not subject to validation. Each item is answered on a 5-point scale, and the average of them is
210 used as the final calculated score (some items are reverse coded). A further three questions
211 with yes/no responses asking them whether they had been vaccinated against covid-19, tested
212 positive for covid-19 or believed they had previously contracted covid-19. Finally, we asked
213 participants to answer two questions taken from Lazarus et al. [7] to measure potential
214 acceptance of a covid-19 vaccine; "if a COVID-19 vaccine is proven safe and effective and is
215 available, I will take it." and "You would accept a vaccine if it were recommended by your
216 employer and was approved safe and effective by the government." They were answered on a
217 5-point scale from strongly disagree to strongly agree, and the average of the two answers was
218 calculated for analysis.

219

	Good	Bad
Technical	Vaccines reduce risks of contracting a disease by working with your physiology to increase protection. They work by triggering a physiological immune response within the body. This happens because vaccines contain a harmless form of the virus from the microorganism that causes the disease you are being vaccinated against. These inoculations train the immune system to recognize and combat pathogens such as viruses. Vaccines don't just work at an individual level, they protect entire populations. Once enough people are immunized, opportunities for propagation of the epidemic are reduced so people who aren't immunized benefit. Herd immunity works because if enough people are vaccinated, the risk of the disease being transmitted to people who are not able to be vaccinated is reduced.	Vaccines reduce risks of getting a disease by introducing (subcutaneously or intramuscularly) the vaccine into the body. They work because when you are immunized you have the vaccine physiologically introduced to your body. Vaccines contain a harmless molecular compound , which means that when you are vaccinated you won't catch the disease. Vaccines don't just work at an individual level, they protect entire populations. The inoculated population with the vaccine then benefit from the extensive immunization. Herd immunity works because if enough people have the vaccine introduced to their immune system then it's harder for those people to contract the disease.
Non-technical	Vaccines reduce risks of getting a disease by working with your body's natural defences to build protection. They work by triggering an immune response within the body. This happens because vaccines contain a harmless form of the virus that causes the disease you are being vaccinated against. They train the immune system to recognize and combat viruses. Vaccines don't just work at an individual level, they protect entire populations. Once enough people are immunized, opportunities for an outbreak of disease are reduced so people who aren't immunized benefit. Herd immunity works because if enough people are vaccinated, it's harder for the disease to spread to people who aren't vaccinated.	Vaccines reduce risks of getting a disease by introducing the vaccine into the body. They work because when you are immunized you have the vaccine in your body. Vaccines contain a harmless substance which means that when you are vaccinated you won't catch the disease. Vaccines don't just work at an individual level, they protect entire populations. The population with the vaccine then benefit from the immunization. Herd immunity works because if enough people are vaccinated then it's harder for those people to get the disease.

220 **Table 2.** An example set of statements (version 1 of 2) given to participants depending on group allocation.
221

222 Participants only read one explanation. The additional technical language that differentiates the technical from
223 the non-technical statements have been emphasized here for clarity, but participants did not see such markings.
224 Version 2 is available in osf.

225

226 **Results**

227 We analysed the data using linear regressions using the *lm* function in R 4.0.3 [19]. All the
228 scripts, outputs, and raw anonymized data for the analyses are available online on osf.
229 Summaries of all experimental variables captured can be found in supplemental material.

230

231 How good and how satisfying

232 We tested for an influence of technical language on participant ratings of 'how good' and 'how
233 satisfying' the explanations were. We used two separate regressions, with the dependent

234 variable for each taken from Question 2; ‘how good is this explanation?’ (HowGood), and
 235 Question 3, ‘how satisfying is this explanation’ (HowSatisfying). The two categorical
 236 predictors were the experimental manipulations of the statements: Quality (Good vs. Bad),
 237 Language (Technical vs. Non-Technical), and their interaction. Both were coded with
 238 treatment (i.e., dummy) contrasts, with the control conditions being Good and Non-Technical.
 239 The coefficients shown in Table 3 are for the treatment conditions (Bad and Technical) in
 240 comparison to the control.

	(3A) How Good		(3B) How Satisfying		(3C) Vaccine Likelihood	
	coefficient (SE)	95% CI	coefficient (SE)	95% CI	coefficient (SE)	95% CI
Intercept	6.35*** (0.08)	[6.19, 6.50]	5.91*** (0.09)	[5.74, 6.08]	5.00*** (0.08)	[4.85, 5.16]
Quality=Bad	-0.99*** (0.11)	[-1.21, -0.77]	-0.89*** (0.12)	[-1.13, -0.65]	-0.24* (0.11)	[-0.03, -0.46]
Language=Technical	-0.24* (0.11)	[-0.46, -0.02]	-0.24* (0.12)	[-0.00, -0.49]	-0.07 (0.11)	[-0.29, 0.15]
Quality=Bad × Language=Technical	0.59*** (0.16)	[0.28, 0.91]	0.54** (0.17)	[0.20, 0.88]	0.11 (0.11)	[-0.20, 0.42]
N	996		996		996	
Adjusted R ²	0.080		0.055		0.003	

241 Note: * p<.05, ** p<.01, *** p<.001
 242

243 **Table 3.** Regression results for How Good, How Satisfying, and Vaccine Likelihood (Δ VL). Coefficient b,
 244 standard error (SE) and 95% Confidence Intervals shown. Quality and Language were dummy coded with the
 245 control (base) being Quality=Good and Language=Non-Technical, and the treatment being Quality=Bad and
 246 Language=Technical.

247
 248 Results were consistent for evaluations of both how good and how satisfying the explanations
 249 were (Tables 3A and 3B). The coefficients for bad Quality were significant and negative for
 250 both dependent variables (Table 3A and 3B). Participants considered the bad statements
 251 without technical language to be worse and less satisfying than the good statements without
 252 technical language.

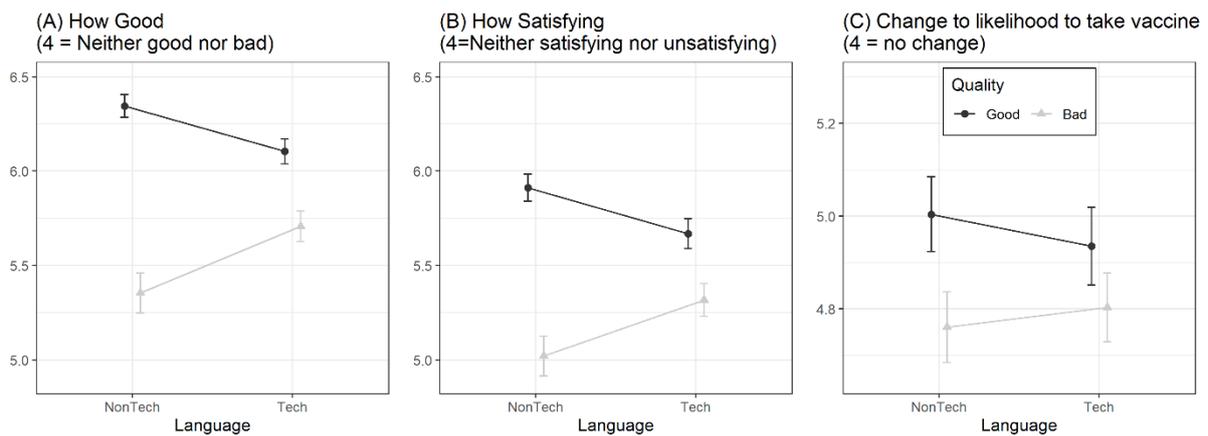
253
 254 The coefficients for technical Language were also significant and negative for both dependent
 255 variables, and the coefficients for the interaction between bad Quality and technical Language
 256 were significant and positive for both dependent variables. A post-hoc pairwise comparison

257 test showed that while the addition of technical language to good statements made them worse
 258 and less satisfying (HowGood: $b=-0.24$, $SE=0.11$, $CI=[-0.46, -0.02]$, $t(992)=2.11$, $p=.035$;
 259 HowSatisfying: $b=-0.24$, $SE=0.12$, $CI=[-0.49, -0.002]$, $t(992)=1.98$, $p=.048$), the addition of
 260 technical language to bad statements made them better and more satisfying (HowGood: $b=0.35$,
 261 $SE=0.11$, $CI=[0.13, 0.57]$, $t(992)=3.11$, $p=.002$; HowSatisfying: $b=0.30$, $SE=0.12$, $CI=[0.06$,
 262 $0.54]$, $t(992)=2.42$, $p=.02$), thereby confirming the existence of a seductive allure effect for bad
 263 statements (Figure 1).

264

265 To check that the observed pattern of findings was evident in both versions of the vignettes we
 266 also re-evaluated all the regressions including Version as an additional categorical variable and,
 267 confirming the consistency of the effects of our manipulations across materials, found no
 268 significant effect of Version or any interactions in any of the analyses (detailed results in osf).
 269 This allows us to conclude that any subsequent observed effects are unlikely to be due to any
 270 idiosyncratic features of the wording used in the vignettes.

271



272

273 **Figure 1.** Mean and standard errors for each grouping of participants for (A) How good, and (B) How satisfying
 274 the explanations were rated, and (C) how likely participants were to change their vaccination intentions after
 275 reading the information.

276 Change to vaccination likelihood

277 We next sought to test if the addition of technical language to good and bad explanations
278 affected participants' likelihood to get vaccinated. The dependent variable for this regression
279 was Question 1: 'after reading this explanation would you be more or less likely to take a
280 COVID-19 vaccine' (Δ VL). The two categorical predictors were the same as above: Quality
281 (Good vs. Bad), Language (Technical vs. Non-Technical), and their interaction. A subsequent
282 evaluation of the influence of Version resulted in no additional significant effects again
283 confirming that the specifics of the wording of the vignettes didn't affect our findings.

284

285 Confirming that explanations can influence behavioural intentions, the coefficient for bad
286 Quality was significant and negative, with lower likelihood to vaccinate for bad explanations
287 without technical language in comparison to good explanations without technical language
288 (Table 3C). The coefficients for Language Technical and the interaction with Quality were not
289 significant. This suggests that only Quality of vaccination statements and not the presence or
290 absence of technical language had a direct effect on changing participants' behavioural
291 intentions to take the covid-19 vaccine.

292 Model with covariates

293 In order to test if the relationships between our experimental manipulations and HowGood,
294 HowSatisfying, and Δ VL were themselves influenced by any of the demographic variables
295 (provided by Prolific Academic), we re-ran the model above adding Acceptance, HadCovid,
296 TestedPositive, and all the demographics (age, gender, education as university degree or no
297 university degree) as covariates. Furthermore, we also added HowGood and HowSatisfying as
298 covariates to the Δ VL model to investigate how those variables influence the likelihood to get
299 vaccinated. To avoid adding highly correlated variables simultaneously into the model, we
300 created two new variables: Good+Satisfying, which was the sum of HowGood and
301 HowSatisfying; and Covid+Positive, which was the sum of HadCovid and TestedPositive.

302

303 Details of the analysis and findings can be found in supplemental material. Crucially, the
304 addition of demographics did not remove the influence of Quality, the vaccine allure effect and
305 the interaction between Quality and Language for HowGood and HowSatisfying (see
306 supplemental materials Table S3A and S3B). In contrast, for the Δ VL regression, the
307 coefficient for Quality was no longer significant (see supplemental materials Table S3C),
308 indicating a potential mediation effect of Good+Satisfying and Acceptance on the relationship
309 between the experimental manipulations and Δ VL (see next section on indirect effect of
310 experimental manipulations).

311

312 Indirect effect of experimental manipulations

313 In the regression with ‘Change to vaccination likelihood’ (Δ VL) as the outcome variable, only
314 Quality of vaccination statements had a direct effect on a change in participants’ behavioural
315 intentions to take the covid-19 vaccine (supplemental materials Table SC). Further, in the
316 regression with ‘How Good’ and ‘How Satisfying’ as outcome variables (Table 3A and 3B)
317 the addition of technical language to good statements made them worse and less satisfying
318 whereas the addition of technical language to bad statements made them better and more
319 satisfying. These findings taken together prompted us to conduct an exploratory analysis and
320 test for an indirect effect of the experimental manipulations on a change in vaccination
321 likelihood via, the sum of participants ratings of how good and how satisfying they found the
322 explanations¹. Despite the lack of any direct interaction effect of Quality and Language on
323 behavioural intentions, the possibility nevertheless remains that our experimental

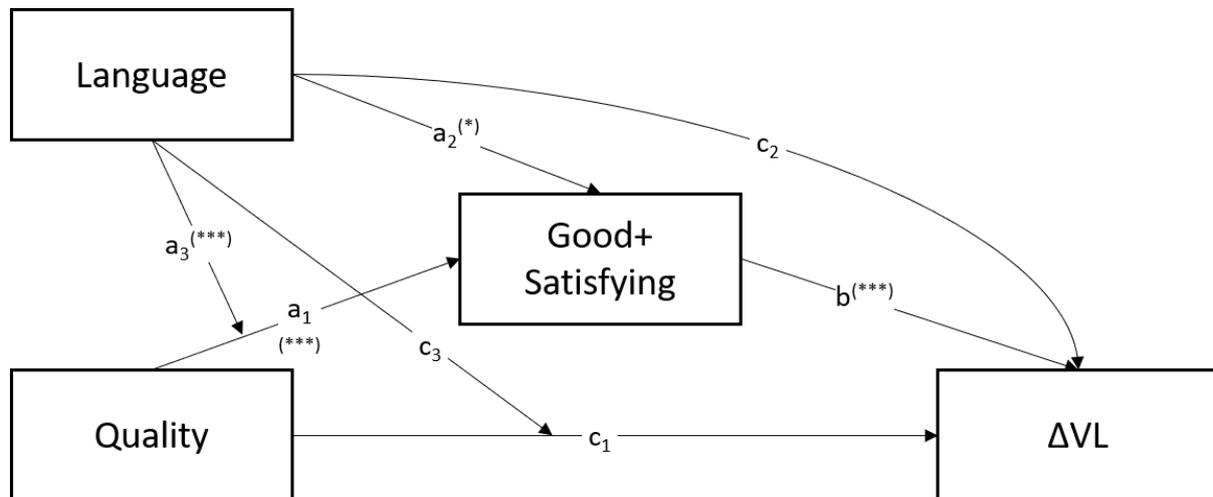
¹ We also tested for indirect effects of Acceptance, but these were not statistically significant (results in osf).

324 manipulations, which influenced how good and how satisfying individuals perceived the
 325 statements to be, in turn influenced participants' likelihood to get vaccinated (Figure 2).

326

327 To investigate this possibility we used a nonparametric percentile bootstrap resampling method
 328 to calculate the means and confidence limits of the coefficients of the indirect effects [20]. The
 329 two models specified in Table 4 were each re-run 10,000 times by drawing random bootstrap
 330 resamples with replacement from the original data, each with a size of $N=996$. For each
 331 resample, the values for the coefficients a_1 , a_2 , and a_3 for Model 4A and the value of b for Model
 332 4B were extracted. The indirect effects were calculated for each experimental manipulation
 333 and their interactions as $a_i \times b$ for each resample. An indirect effect is considered to be present
 334 if the 95% bootstrap confidence limit for the indirect effect does not contain zero.

335



336

337 **Figure 2.** Indirect effects of Good+Satisfying. ΔVL = Change to vaccination likelihood. * $p < .05$, *** $p < .001$.

338 We found three indirect effects significantly different from zero. The indirect coefficient for
 339 bad Quality (Quality=Bad: $a_1 \times b = -0.22$, $CI = [-0.30, -0.15]$), the indirect coefficient for
 340 Language (Language=Technical: $a_2 \times b = -0.06$, $CI = [-0.01, -0.10]$), and the indirect coefficient
 341 for the interaction between bad Quality and technical Language (Quality=Bad \times
 342 Language=Technical: $a_3 \times b = 0.13$, $CI = [0.06, 0.22]$). Because the direct effect of Quality on

343 Δ VL is no longer significant in the model with mediation (Table 4B), there is evidence that the
344 effect of the Quality manipulations on Δ VL was completely mediated by Good+Satisfying. In
345 fact, the indirect effect of bad Quality (-0.22) is very close to the total effect observed in Table
346 3C (-0.24), as expected in cases of complete mediation. In addition, there were significant
347 indirect effects of bad Quality and the interaction between bad Quality and Language Technical
348 on Δ VL, even though there were no direct interaction effects observed in the original model.²
349 This indeed indicates that our experimental manipulations influenced participants' evaluation
350 of the explanations that, in turn, then affected a change in their likelihood to get vaccinated.
351
352 Specifically, the mediation analysis shows a vaccine allure effect on Δ VL: The addition of
353 technical terms to statements of bad Quality had a modest but significant indirect effect (i.e.,
354 $(a_2+a_3) \times b$) of increasing the change to vaccination likelihood by 0.08 (CI=[0.02, 0.14])
355 compared to statements with no technical language, mediated by the combined higher values
356 of good and satisfying ratings. In sum, this analysis shows that including technical language
357 modified participants' evaluation of the explanations, which in turn influenced a likelihood to
358 vaccinate.
359

	(4A) Good+Satisfying		(4B) Vaccine Likelihood	
	coefficient	SE	coefficient	SE
Intercept	12.16***	(0.16)	3.58***	(0.20)
Quality=Bad	(a ₁) -1.88***	(0.22)	(c ₁) -0.02	(0.11)
Language=Technical	(a ₂) -0.48*	(0.22)	(c ₂) -0.01	(0.11)
Quality=Bad x Language=Technical	(a ₃) 1.13***	(0.31)	(c ₃) -0.02	(0.15)
Good+Satisfying			(b) 0.12***	(0.02)

360 Note: * p<.05, ** p<.01, *** p<.001

361 **Table 4.** Models for the calculation of the indirect effects of Good+Satisfying on Vaccine Likelihood.

362
363 **Discussion**

² While traditionally mediation is only considered when there is a direct effect to be mediated, many authors have advocated that the presence of a direct effect is not required before assessing and interpreting indirect effects [37,38].

364 This study demonstrates the seductive allure effect for bad explanations and interestingly a
365 reversed ‘seductive allure’ effect when participants are presented with good explanations – a
366 ‘repellent disdain’ effect. Specifically, we replicate previous findings showing that the
367 inclusion of technical terminology has a typical seductive allure effect on people’s rating of
368 ‘bad’ vaccine explanations [14,15,17]. That is, bad explanations with technical language are
369 judged as better and more satisfying compared to bad explanations without technical language.
370 Interestingly, good explanations of vaccines are rated as worse and less satisfying when
371 participants read an explanation containing technical language.

372

373 Importantly, here, we extend the research on evaluating explanations to include an
374 understanding of how judgments affect behavioural intentions to take up a vaccine. Crucially,
375 participants who read good explanations indicated that they were more likely to take up a covid-
376 19 vaccination than those who read bad explanations. Furthermore, our indirect effects analysis
377 showed that the effect on evaluations of the explanations influenced intentions to vaccinate.
378 Our findings effectively demonstrate that the better evaluation of bad explanations with
379 technical language, compared to those without technical language, and the worse evaluation of
380 good explanations with technical language, compared to those without technical language,
381 subsequently and differentially influenced intentions to vaccinate. Crucially, previous research
382 examining intentions to vaccinate show that intentions are closely associated with actual
383 vaccine acceptance and that intentions to vaccinate likely play a causal role in behaviour [21–
384 23]. Nevertheless, the policy implications of our findings would be strengthened by future work
385 that took a measure of actual behaviour and confirmed a change in vaccination rates as a result
386 of experimental manipulations.

387

388 In considering our novel finding that good explanations were rated as worse when they
389 included technical language we note that, in the original paper reporting a seductive allure
390 effect of neuroscience terms on psychological explanations, Weisberg et al. [17] found no
391 effect of technical language on good explanations in their lay sample. However, Weisberg et
392 al. [17] report that their neuroscience experts rated good explanations as significantly less
393 satisfying when they contain neuroscience jargon; akin to our finding in a typical population.
394 This reverse allure effect for good explanations hasn't been reported elsewhere but this
395 direction of effect is observable in more recent research [17]. Our finding may, at least in part,
396 be due to the notable increase in power our study has compared to previous studies [14,15,17].

397

398 It is possible that the circumstances of the pandemic provided us with a sample of participants
399 that, on the subject of vaccination, differ qualitatively from previous research on the seductive
400 allure effect. That is, the ubiquity of reporting on the pandemic, that has included detailed
401 technical and epidemiological information, has inculcated a level of 'lay expertise' among the
402 general population. Lay expertise effects have, for example, been observed in patient groups
403 without formal medical education (e.g.,[24]) and might account for why good explanations are
404 obscured by irrelevant technical information, such that our participants performed similarly to
405 the experts in earlier studies [14].

406

407 As with previous findings [14,15], the inclusion of technical language in bad explanations
408 'seduced' our participants, who rated those explanations as better and more satisfying than
409 those who read bad explanations without technical language. This suggests that the inclusion
410 of technical language in bad explanations has the effect of irrationally improving evaluations
411 of messages that lacks any explanatory power. In previous research, the effect that technical or

412 reductive language has on ‘good’ explanations is far less reliable and varies across papers and
413 populations [14,15,17].

414

415 An alternative account for our findings, but one that explains both the beneficial effect of
416 technical language on bad explanation and its negative impact on good explanations, may lie
417 in the seductive effect of details (see, [25] and [26]). This concept suggests that technical
418 language distracts from the content of the information. In our data, it may be that technical
419 language distracted from the appreciation of clear explanatory information in the good
420 condition and distracted from the detection of tautological and ill-posed information in the bad
421 condition. Moreover, our participants were evaluating explanations on a subject they were
422 highly aware of and that had great immediate relevance to their daily lives. This knowledge of
423 the subject and familiarity with some technical jargon, given its ubiquity in the media, may
424 have rendered participants’ attention more easily drawn to the technical terms which, in turn,
425 could distract more from appreciation of the quality of the explanation, good or bad.

426

427 The seductive allure effect bears comparison with the observation that people are susceptible
428 to “pseudo-profound bullshit” [27,28] whereby seemingly impressive assertions presented as
429 true and meaningful, but that are actually vacuous, are judged to be profound. Bullshit
430 receptivity manifests as a reliable personal characteristic reflective of cognitive style:
431 negatively correlated with verbal and fluid intelligence and cognitive reflection and positively
432 correlated with conspiracy beliefs and confirmation bias [29]. Such effects may well contribute
433 to the illusion of explanatory depth [30,31] when people confidently believe they understand a
434 concept more deeply than they actually do. The primary aim of our study was not to inform
435 understanding of the underlying cognitive mechanism that produce the observed effects, rather,
436 by demonstrating a link between the effect of technical language on behavioural intentions, we

437 hope to inform public health campaigns and increase public understanding of science.
438 Nevertheless, the results pose interesting questions for future research regarding the underlying
439 cognitive processes involved.

440

441 One limitation of, and a further possible explanation for our findings, is that ratings and
442 vaccination intentions may have been affected by the word length of the explanations. Good
443 explanations were on average longer than bad, and technical explanations longer than non-
444 technical. Previous research has shown that longer explanations tend to be rated as better than
445 shorter ones [32,33]. Although this could explain why good explanations and technical
446 explanations were rated as better and resulted in greater intentions to vaccinate overall, this
447 account cannot explain the opposite effects observed on good and bad explanations when
448 technical language is included; word length cannot account for the critical interaction effect
449 observed in our data.

450

451 We observed a direct effect of quality manipulations on people's behavioural intentions to
452 vaccinate – good explanations increased intentions compared to bad. Moreover, we also
453 revealed clear evidence for an indirect effect of the influence of our manipulations on people's
454 intentions to take a COVID-19 vaccine. This was mediated via the direct effect of our
455 experimental manipulations on people's evaluations of the explanations. Given the effect on
456 behavioural intentions to vaccinate, our data have implications for public health endeavours.
457 Specifically, as good quality explanations are made worse and subsequently negatively affect
458 intentions to vaccinate, public health communication should favour commonly used and non-
459 technical language. Previous research that has explored clarity in public health messaging has
460 argued messaging should always use the language used by the primary audience [34]. Here we

461 can expand on this recommendation by suggesting that if less scientific and more frequently
462 used words are available to explain and describe, they should be used.

463

464 Our tautological explanations were not written to mislead people and cannot be classed as
465 misinformation. Nevertheless much misinformation found in a broad array of sources attempts
466 to convey spurious explanations using scientific content [35]. In this respect, our finding that
467 bad – tautological - explanations were perceived as better when accompanied by technical
468 language contributes to our understanding of the influence of misinformation. This finding is
469 in line with others showing that scientific sounding misinformation is perceived as trustworthy
470 and is likely to be shared on social media [11]. Worryingly, the repetition and prevalence of
471 misinformation has been suggested to disproportionately increase belief [36]. Our findings
472 suggest that public health endeavours are at risk of being sabotaged by misinformation that can
473 successfully take advantage of the use of technical language to persuade people to believe ‘bad’
474 explanations.

475

476 Here we showed that the inclusion of technical language in good vaccine explanations not only
477 resulted in participants rating them as worse and less satisfying but importantly also reduces
478 behavioural intentions to vaccinate. This ‘repellent disdain’ effect has significant implications
479 for the public understanding of science and public health communication strategies. While
480 good explanations increase people’s intentions to vaccinate, when good explanations are
481 accompanied with un-necessary technical language they are perceived as worse and this, in
482 turn, causes people to decrease their intentions to vaccinate. The notion that explanations
483 involving more technical language are better, perhaps because they look more ‘scientific’ is
484 not supported by our data. On the contrary, our data suggest that, in communications designed
485 to explain vaccines, any attempt to persuade the public to vaccinate by including technical

486 language is ill advised and that clear, simple, and straightforward information is a better
487 approach to public health information communication. In the specific context of promoting
488 understanding of vaccination understanding and vaccine uptake, we can recommend the use of
489 informative messages that forgo the inclusion of any scientific terminology.

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