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

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Acknowledgements
We thank Dr. Ian L. Jones for his expert advice in constructing the vaccine explanations.

Abstract

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

Introduction

Thanks to monumental and historic efforts, multiple covid-19 vaccinations have now been approved for use in numerous countries and have been shown to be safe and effective [1–3]. These vaccinations are at the heart of the global effort to mitigate the ongoing pandemic. As such, public health interventions and campaigns are focused on increasing public understanding of, and promoting behavioural intentions towards, vaccination.

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

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

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

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

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

In the current study, participants were presented with information about a covid-19 vaccine. We varied the information by manipulating two factors: how good/bad and how technical/non-technical the explanations were. ‘Good’ explanations provided a mechanistic account as to how vaccines and herd immunity works (such as: Vaccines work by triggering an immune response within the body). ‘Bad’ explanations were circular in nature and provided no underlying explanation (such as: Vaccines work because when you are immunized you have the vaccine in your body). ‘Technical’ explanations included technical language irrelevant to the explanation but related to vaccinations and covid-19 (such as reference to “pathogens such as viruses” rather than merely “viruses”). After reading the information we asked participants to rate the explanation they saw in terms of how ‘satisfying’ and how ‘good’ the explanation was (as in [14]) and whether reading the information affected their intention to take a covid-19 vaccine. Finally, we measured vaccine hesitancy dispositions [18]. Exploring how good quality explanations are affected by the addition of technical language provides insight into public health communication. Specifically, we are able to consider whether good explanations should include technical language in descriptions of vaccinations, whether necessary or not, to promote engagement with vaccination programmes. Further, by considering responses to low quality explanations, with and without technical language, we can examine how poorer explanations, such as misinformation, or simply badly communicated information, affects beliefs and behavioural intentions towards vaccines.

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

Methods

Participants

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

	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)

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

Design and Procedure

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

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

	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.

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

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

Results

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

How good and how satisfying

We tested for an influence of technical language on participant ratings of 'how good' and 'how satisfying' the explanations were. We used two separate regressions, with the dependent variable for each taken from Question 2; ‘how good is this explanation?’ (HowGood), and Question 3, ‘how satisfying is this explanation’ (HowSatisfying). The two categorical predictors were the experimental manipulations of the statements: Quality (Good vs. Bad), Language (Technical vs. Non-Technical), and their interaction. Both were coded with treatment (i.e., dummy) contrasts, with the control conditions being Good and Non-Technical. The coefficients shown in Table 3 are for the treatment conditions (Bad and Technical) in 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	

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

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

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

The coefficients for technical Language were also significant and negative for both dependent variables, and the coefficients for the interaction between bad Quality and technical Language were significant and positive for both dependent variables. A post-hoc pairwise comparison test showed that while the addition of technical language to good statements made them worse and less satisfying (HowGood: b=-0.24, SE=0.11, CI=[-0.46, -0.02], t(992)=2.11, p=.035; HowSatisfying: b=-0.24, SE=0.12, CI=[-0.49, -0.002], t(992)=1.98, p=.048), the addition of technical language to bad statements made them better and more satisfying (HowGood: b=0.35, SE=0.11, CI=[0.13, 0.57], t(992)=3.11, p=.002; HowSatisfying: b=0.30, SE=0.12, CI=[0.06, 0.54], t(992)=2.42, p=.02), thereby confirming the existence of a seductive allure effect for bad statements (Figure 1).

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

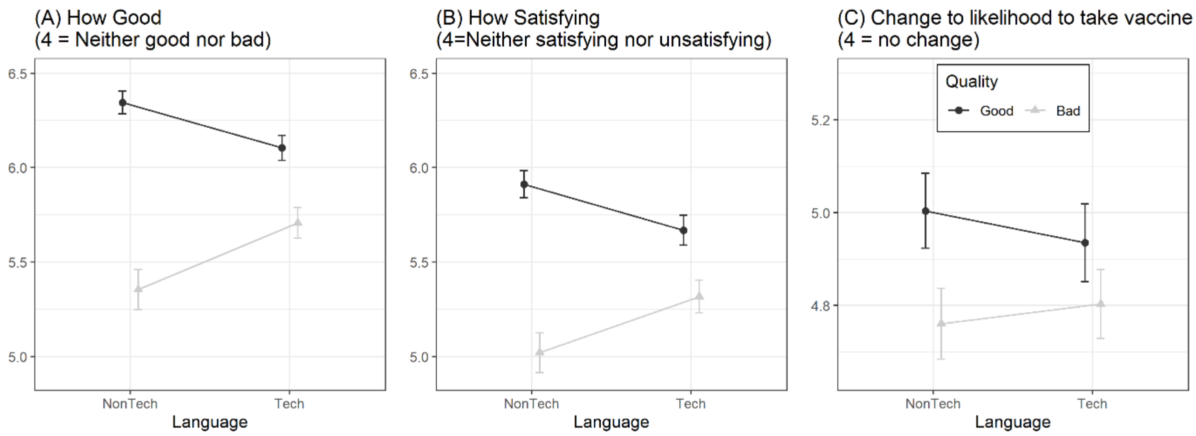

Figure 1. Mean and standard errors for each grouping of participants for (A) How good, and (B) How satisfying the explanations were rated, and (C) how likely participants were to change their vaccination intentions after reading the information.

Change to vaccination likelihood

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

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

Model with covariates

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

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

Indirect effect of experimental manipulations

In the regression with 'Change to vaccination likelihood' (ΔVL) as the outcome variable, only Quality of vaccination statements had a direct effect on a change in participants' behavioural intentions to take the covid-19 vaccine (supplemental materials Table SC). Further, in the regression with 'How Good' and 'How Satisfying' as outcome variables (Table 3A and 3B) the addition of technical language to good statements made them worse and less satisfying whereas the addition of technical language to bad statements made them better and more satisfying. These findings taken together prompted us to conduct an exploratory analysis and test for an indirect effect of the experimental manipulations on a change in vaccination likelihood via, the sum of participants ratings of how good and how satisfying they found the explanations[1]. Despite the lack of any direct interaction effect of Quality and Language on 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).

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

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

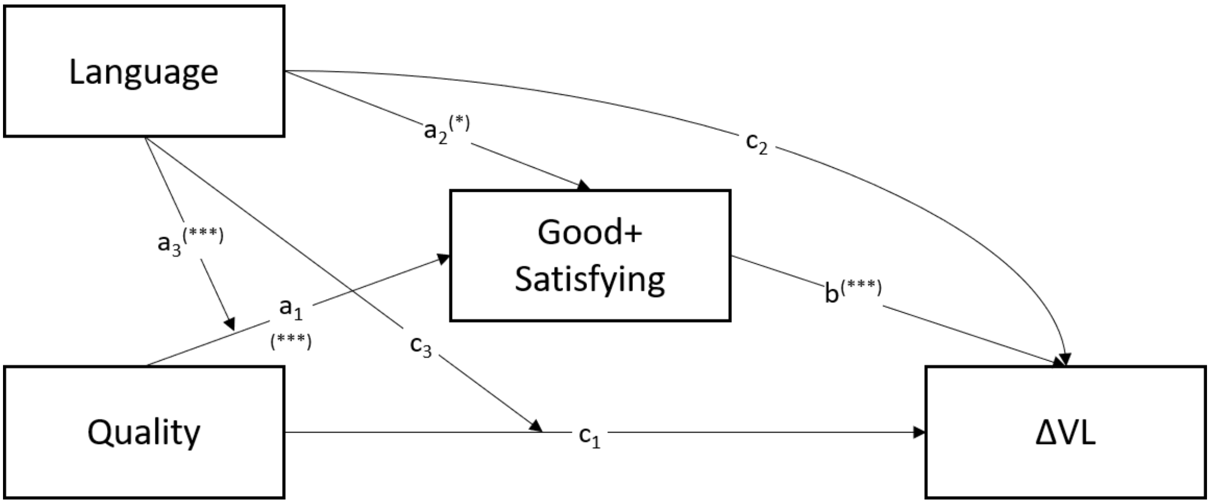

Figure 2. Indirect effects of Good+Satisfying. ΔVL = Change to vaccination likelihood. * p < .05, *** p < .001.

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

ΔVL is no longer significant in the model with mediation (Table 4B), there is evidence that the effect of the Quality manipulations on ΔVL was completely mediated by Good+Satisfying. In fact, the indirect effect of bad Quality (-0.22) is very close to the total effect observed in Table 3C (-0.24), as expected in cases of complete mediation. In addition, there were significant indirect effects of bad Quality and the interaction between bad Quality and Language Technical on ΔVL, even though there were no direct interaction effects observed in the original model.[2] This indeed indicates that our experimental ma nipulations influenced participants' evaluation of the explanations that, in turn, then affected a change in their likelihood to get vaccinated.

Specifically, the mediation analysis shows a vaccine allure effect on ΔVL: The addition of technical terms to statements of bad Quality had a modest but significant indirect effect (i.e., $(a_2+a_3) \times b$) of increasing the change to vaccination likelihood by 0.08 (CI=[0.02, 0.14]) compared to statements with no technical language, mediated by the combined higher values of good and satisfying ratings. In sum, this analysis shows that including technical language modified participants' evaluation of the explanations, which in turn influenced a likelihood to vaccinate.

	(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 × Language=Technical	(a_3) 1.13***	(0.31)	(c_3) -0.02	(0.15)
Good+Satisfying			(b) 0.12***	(0.02)

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

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

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].

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

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

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

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

As with previous findings [14,15], the inclusion of technical language in bad explanations 'seduced' our participants, who rated those explanations as better and more satisfying than those who read bad explanations without technical language. This suggests that the inclusion of technical language in bad explanations has the effect of irrationally improving evaluations of messages that lacks any explanatory power. In previous research, the effect that technical or reductive language has on ‘good’ explanations is far less reliable and varies across papers and populations [14,15,17].

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

The seductive allure effect bears comparison with the observation that people are susceptible to “pseudo-profound bullshit” [27,28] whereby seemingly impressive assertions presented as true and meaningful, but that are actually vacuous, are judged to be profound. Bullshit receptivity manifests as a reliable personal characteristic reflective of cognitive style: negatively correlated with verbal and fluid intelligence and cognitive reflection and positively correlated with conspiracy beliefs and confirmation bias [29]. Such effects may well contribute to the illusion of explanatory depth [30,31] when people confidently believe they understand a concept more deeply than they actually do. The primary aim of our study was not to inform understanding of the underlying cognitive mechanism that produce the observed effects, rather, by demonstrating a link between the effect of technical language on behavioural intentions, we hope to inform public health campaigns and increase public understanding of science. Nevertheless, the results pose interesting questions for future research regarding the underlying cognitive processes involved.

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

We observed a direct effect of quality manipulations on people's behavioural intentions to vaccinate – good explanations increased intentions compared to bad. Moreover, we also revealed clear evidence for an indirect effect of the influence of our manipulations on people's intentions to take a COVID-19 vaccine. This was mediated via the direct effect of our experimental manipulations on people's evaluations of the explanations. Given the effect on behavioural intentions to vaccinate, our data have implications for public health endeavours. Specifically, as good quality explanations are made worse and subsequently negatively affect intentions to vaccinate, public heath communication should favour commonly used and non-technical language. Previous research that has explored clarity in public health messaging has argued messaging should always use the language used by the primary audience [34]. Here we can expand on this recommendation by suggesting that if less scientific and more frequently used words are available to explain and describe, they should be used.

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

Here we showed that the inclusion of technical language in good vaccine explanations not only resulted in participants rating them as worse and less satisfying but importantly also reduces behavioural intentions to vaccinate. This 'repellent disdain' effect has significant implications for the public understanding of science and public health communication strategies. While good explanations increase people's intentions to vaccinate, when good explanations are accompanied with un-necessary technical language they are perceived as worse and this, in turn, causes people to decrease their intentions to vaccinate. The notion that explanations involving more technical language are better, perhaps because they look more 'scientific' is not supported by our data. On the contrary, our data suggest that, in communications designed to explain vaccines, any attempt to persuade the public to vaccinate by including technical language is ill advised and that clear, simple, and straightforward information is a better approach to public health information communication. In the specific context of promoting understanding of vaccination understanding and vaccine uptake, we can recommend the use of informative messages that forgo the inclusion of any scientific terminology.

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