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

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Abstract

Background: Previous research has demonstrated a ‘seductive allure’ of technical or reductive language. Specifically, bad explanations – i.e., those presenting circular restatements of a phenomenon or other non-explanatory information – are judged better explanations when irrelevant technical language is included.

Methods: Using a between subjects design we presented participants (N=996) with one of four possible vignettes that explain how covid-19 vaccinations and herd immunity works. The explanations varied along two factors: (1) Quality, explanations were either good or bad (tautological); (2) Language, explanations either contained unnecessary technical language or did not. We measured participants’ evaluation of the explanations (‘how good’ and ‘how satisfying’ they were) and subsequent intentions to vaccinate.

Results: We demonstrate a novel ‘seductive allure’ effect of technical language on vaccine information. Including unnecessary technical language in informative explanations resulted in them being judged worse. However, including irrelevant technical terminology in bad quality explanations resulted in them being judged better. Importantly, we also observe indirect effects of the evaluation of explanations on behavioural intentions to vaccinate.

Conclusions: We show that explanatory public health information that omits reductive technical language is more effective in increasing public intentions to vaccinate. We also suggest that misinformation that includes technical language could be more detrimental to vaccination rates.

Keywords

Seductive allure; covid-19; vaccination intentions; vaccine hesitancy

Introduction

Global efforts to counter the covid-19 pandemic have, for the first time, involved non-pharmaceutical interventions (NPIs) on a global scale. Ongoing evaluation of NPIs, including restricting movement of people, closure of schools and workplaces, and the implementation of masks in public spaces, have shown that they are an effective measure to reduce transmission, subsequent hospitalisation and mortality rates (Bo et al., 2021; Flaxman et al., 2020; Imai et al., 2020; Lai et al., 2020). However, the majority of adopted NPIs have tangible social, economic and mental health implications that mean their implementation is not consequence free (Seale et al., 2020). Thanks to monumental and historic efforts, multiple vaccinations have now been approved for use in numerous countries and have been shown to be safe and effective (Mahase, 2020; Polack et al., 2020; Voysey et al., 2021). As such, public health interventions in the form of NPIs turn their efforts to 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 (*Ten Threats to Global Health in 2019*). 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 in the broader population (Smith, 2017). Hesitancy about covid-19 vaccinations is prevalent in the population with approximately 28% of the UK population either very unsure or strongly hesitant to accept a covid-19 vaccine (Freeman et al., 2020). Research on a global scale surveying 19 countries strongly impacted by the pandemic identified that, in June 2020, willingness to accept a covid-19 vaccine varied considerably but is insufficient in most to achieve coverage and community immunity (Lazarus et al., 2020). Lazarus et al. (2020) found that only 75.4% of respondents in the USA responded indicating they would accept a covid-19 vaccine, compared to 54.9% in Russia and 88.6% in China.

Public health interventions in the form of both NPIs and vaccination depend on the public engaging with the interventions which in turn requires effective dissemination of information and communication to persuade and co-ordinate the public response. Sometimes confounding this goal, the ubiquity of social media has been linked to the spread and prevalence of *misinformation*, directly impacting public health measures (Chou et al., 2018). Loomba et al. (2020) 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. (2020) also suggest that misinformation purporting to be based in science has a particularly damaging effect on vaccination intentions.

Misinformation is not necessarily explicitly false or incorrect but may contain ‘misleading content’ that, for example, reformulates or re-contextualises selected details (Brennen et al., 2020). 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 (Zingg & Siegrist, 2012) there is a clear rationale for determining effective ways to communicate vaccine knowledge.

In the current research we borrow an idea that has explored how people engage with explanatory scientific information and whether reductive or technical language obfuscates understanding; commonly referred to as a ‘seductive allure’. Initially reported in the field of psychology and neuroscience, the ‘seductive allure’ effect shows a reduction in participants’ ability to differentiate good from bad explanations of psychological phenomena when irrelevant neuroscientific terms are included (Weisberg et al., 2008). Subsequent research has demonstrated that 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 (Hopkins et al., 2016). Very little research has explored whether the inclusion of unnecessary terminology has any effect on behavioural intentions (e.g., Saporta, 2020) and this has yet to be explored in the context of health behaviours.

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 Weisberg et al., 2008) and whether reading the information affected their intention to take a covid-19 vaccine. Finally, we measured vaccine hesitancy dispositions (Shapiro et al., 2018).

We expected to replicate previous ‘seductive allure’ findings and demonstrate that the inclusion of technical language enhanced the ratings of bad explanations more than it enhanced the ratings of good explanations, thereby reducing the difference between participants’ ratings of good and bad explanations. We also expected that good, compared to bad explanations, would increase the intention to vaccinate. Moreover, if technical information also has a ‘seductive’ effect on behavioural intentions then we would expect those exposed to explanations with irrelevant scientific terms to differ less in their intention when exposed to good compared to bad explanations.

Whilst public health bodies are expected to provide good clear information about vaccinations it remains unknown as to whether the inclusion of scientific technical terms influences intentions to vaccinate. Furthermore, we might better understand the nature of misinformation and its effect on vaccination intentions – are poor explanations more influential when littered with irrelevant scientific information?

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. 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 for a description of participant socio-demographic information.

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

	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)

Design and Procedure

Participants were presented with a short explanation about how vaccination, immunisation and herd immunity works. The explanation was either good or bad and either contained technical language or did not, forming four possible categories that were 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; www.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”, possible responses were given on a 7-point scale from very unlikely to very likely, with the middle point indicating no change. 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 (Weisberg et al., 2008). After answering these questions participants were asked to ignore the information presented in the explanation and complete the Vaccine Hesitancy Scale (VHS; Shapiro et al., 2018). 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 and make it more appropriate for the survey respondents. Each item is answered on a 5-point scale, and the average between 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. (2020) 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.

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.

	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.

Results

Summaries of all experimental variables captured are shown in Table 3. We analysed the data using linear regressions using the *lm* function in R 4.0.3 (R Core Team, 2020). All the scripts, outputs, and raw anonymized data for the analyses are available online on osf.

Table 3. Experimental variables captured. VHS is the average between 10 questions. Vaccine acceptance is the average between two questions.

Means (SD) [Possible range of values in brackets]	Good		Bad	
	Non- Technical	Technical	Non-Technical	Technical
Q1. Change to vaccination likelihood (Δ VL) [1-7]	5.00 (1.27)	4.94 (1.31)	4.76 (1.20)	4.80 (1.16)
Q2. How good (HowGood) [1-7]	6.35 (0.95)	6.11 (1.05)	5.35 (1.66)	5.71 (1.28)
Q3. How satisfying (HowSatisfying) [1-7]	5.91 (1.13)	5.67 (1.25)	5.02 (1.67)	5.32 (1.37)
Q4. Vaccine Hesitancy Scale (VHS) [1-7]	4.15 (0.61)	3.99 (0.68)	4.06 (0.65)	4.02 (0.68)
Q5. Vaccine Acceptance (Acceptance) [1-7]	4.37 (0.94)	4.19 (1.07)	4.25 (1.05)	4.22 (1.03)

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 4 are for the treatment conditions (Bad and Technical) in comparison to the control.

Table 4. Regression results for How Good, How Satisfying, and Vaccine Likelihood (Δ VL). 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.

	(4A) How Good		(4B) How Satisfying		(4C) 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 x 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: * $p < .05$, ** $p < .01$, *** $p < .001$

Results were consistent for evaluations of both how good and how satisfying the explanations were (Tables 4A and 4B). The coefficients for bad Quality were significant and negative for both dependent variables (Table 4A and 4B). 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.

The coefficients for the interaction between bad Quality and technical Language were both significant and positive. 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 (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).

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 changed 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.

Confirming that explanations can influence behavioural intentions the coefficient for bad Quality was significant and negative, with lower likelihood to vaccinate for bad explanation without technical language in comparison to good explanations without technical language (Table 4C). 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

To test if the relationships between our experimental manipulations and HowGood, HowSatisfying, and Δ VL were themselves influenced by any of the demographic variables (provided by Prolific Academic), we re-ran the model above adding VHS, Acceptance, and all the demographics from Table 1 as covariates. Furthermore, we also added HowGood and HowSatisfying as covariates to the Δ VL model to investigate how those variables influence the change to likelihood to get vaccinated.

First, we evaluated the correlations between all the predictors because we did not want to add variables that were highly correlated amongst themselves to the regression, as this introduces multi-collinearity and generates unreliable coefficient estimates. We found that two pairs of variables were highly correlated. First, the variables HowGood and HowSatisfying had a Pearson correlation of $r=0.77$. Second, the variables HadCovid and TestedPositive had a polychoric correlation of $\rho=0.79$. All other absolute correlations were smaller than 0.20. To avoid adding highly correlated variables simultaneously into the model, we created two new variables instead: Good+Satisfying, which is the sum of HowGood and HowSatisfying; and Covid+Positive, which is the sum of HadCovid and TestedPositive.

Table 5. Regression results for How Good, How Satisfying, and Vaccine Likelihood (Δ VL). Coefficient b, standard error (SE) and 95% Confidence Intervals shown.

	(5A) How Good		(5B) How Satisfying		(5C) Vaccine Likelihood	
	coefficient	SE	coefficient	SE	coefficient	SE
Intercept	4.70***	(0.30)	3.30***	(0.32)	2.79***	(0.31)
Quality=Bad	-0.96***	(0.11)	-0.85***	(0.12)	-0.06	(0.11)
Language=Technical	-0.20	(0.11)	-0.18	(0.12)	-0.00	(0.11)
Quality=Bad x Language=Technical	0.55***	(0.16)	0.49**	(0.17)	0.00	(0.15)
VHS	0.30**	(0.09)	0.41***	(0.10)	0.01	(0.09)
Acceptance	0.10	(0.06)	0.21***	(0.06)	0.32***	(0.06)
Covid+Positive	-0.08	(0.09)	-0.12	(0.09)	-0.10	(0.08)
Employed=Unemployed	-0.14	(0.09)	-0.12	(0.10)	-0.16	(0.09)
Education=NoUniversity	0.20*	(0.08)	0.04	(0.09)	0.18*	(0.08)
Politics=Left	-0.15	(0.09)	-0.25**	(0.09)	-0.20*	(0.08)
Politics=Right	0.10	(0.13)	-0.04	(0.13)	-0.19	(0.12)
Age	0.00	(0.00)	0.01	(0.00)	-0.00	(0.00)
Gender=Male	-0.02	(0.08)	-0.01	(0.09)	-0.06	(0.08)
Good+Satisfying					0.08***	(0.02)
N	995		995		995	
Adjusted R ²	0.122		0.153		0.122	

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

One participant was excluded for not answering the politics question.

From the experimental measurements captured, the coefficient for Good+Satisfying on Δ VL was significant and positive (see Table 5C). For statements that were rated better and more satisfying, participants responded with higher likelihoods to get vaccinated.

The coefficient for Acceptance was also positive and significant in relation to both HowSatisfying and Δ VL. Individuals who reported higher acceptance also rated the statements as more satisfying and responded with higher likelihood to get vaccinated. The coefficient for VHS was significant and positive in relation to both HowGood and HowSatisfying, indicating the participants with lower vaccine hesitancy found the statements better and more satisfying.

Crucially, the addition of demographics did not remove the influence of Quality and the vaccine allure effect (interaction between Quality and Language) for HowGood and HowSatisfying (see Table 5A and 5B). In contrast, for the Δ VL regression, the coefficient for Quality was no

longer significant (see Table 5C), 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).

Amongst the demographics captured, the coefficients for left Politics were significant for HowSatisfying and ΔVL , with individuals on the left spectrum of politics reporting lower satisfaction and lower likelihood to get vaccinated than those in the centre. Finally, the coefficients for Education were significant and positive for HowGood and ΔVL , with individuals who had not completed a university degree rating the statements as better and reporting a higher ΔVL in comparison to those without a degree. Individuals who were less educated appear to have been more capriciously influenced by the statements provided, while those with higher education are likely to have a more developed view.

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 (Table 5C). Further, in the regression with ‘How Good’ and ‘How Satisfying’ as outcome variables (Table 4A and 4B) 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 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 explanations¹. Despite the lack of any direct effects of our manipulations on behavioural intentions, the possibility nevertheless remains that, to the (variable) extent that our experimental manipulations influenced how good and how satisfying individuals perceived the statements to be, this might in turn have 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 (MacKinnon et al., 2004). The two models specified in Table 6 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 6A and the value of b for Model 6B 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.

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

Figure 2. Indirect effects of Good+Satisfying.

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 $\times$ 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 6B), 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 4C (-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 effects observed in the original model.² This indeed indicates that our experimental manipulations influenced participants' evaluation of the explanations that, in turn, then effected 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 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.

Table 6. Models for the calculation of the indirect effects of Good+Satisfying on Vaccine Likelihood

	(6A) Good+Satisfying		(6B) 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 $\times$ Language=Technical	(a ₃) 1.13***	(0.31)	(c ₃) -0.02	(0.15)
Good+Satisfying			(b) 0.12***	(0.02)

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

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 (Hayes, 2009; Zhao et al., 2010).

Discussion

This study shows that the inclusion of technical terminology has a ‘seductive allure’ on people’s rating of vaccine explanations. The interaction between the effects of the quality of explanations, and the presence or absence of technical reductive terms, replicates previous research which has observed a ‘seductive allure’ effect using technical terms in other fields (Hopkins et al., 2016, 2019; Weisberg et al., 2008). However, here, we extend the seductive allure effect to a public health scenario and report evidence that the ‘seductive allure’ effect in turn influences behavioural intentions to take up a covid-19 vaccine.

As in previous findings (Weisberg et al., 2008), 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 information that lacks any explanatory power. However, unlike previous findings (Weisberg et al., 2008), our data suggest that this effect is context dependent; such that explanations that were good, and did contain explanatory information, were rated as worse and less satisfying when participants read a version containing technical language. A possible account for both effects may lie in the seductive effect of details (see, Rey, 2012) such that technical language distracts from the content of the information. In our data, it may be that technical language distracts from clear explanatory information in the good condition and distracts from tautological and ill-posed information in the bad condition.

Our tautological explanations were not misinformation as they were not written to mislead people. Misinformation however, is found in a broad array of sources, many of which attempt to convey explanations using scientific content (Gupta et al., 2020). In this respect, our finding that bad and tautological descriptions were perceived as better when contaminated with technical language contributes to our understanding of the influence of misinformation. This is in line with findings showing that scientific sounding misinformation is perceived as trustworthy and is likely to be shared on social media (Loomba et al., 2020). Our findings suggest that public health endeavours are at risk of being sabotaged by misinformation that can successfully take advantage of using technical language to better persuade people.

Although our manipulations of the quality of explanations and the presence of technical language directly influenced people’s evaluations of how satisfactory and good the explanations were, we did not observe corresponding direct effects on people’s behavioural intentions to vaccinate. Nevertheless, our investigation of the influence of *indirect* effects revealed clear evidence for an indirect effect of seductive allure on people’s intentions to take a COVID-19 vaccine - mediated via the direct effect of our manipulations of the materials on people’s evaluations of the explanations. Variance in the rated quality of the explanations predicted self-reported change in likelihood of taking a COVID-19 vaccine.

In the context of public health interventions, and particularly regarding the pandemic, these findings have clear implications. The value people place on the information they receive about vaccinations affects their behavioural intentions to vaccinate. While good explanations increase people’s intentions to vaccinate, if good explanations are accompanied with unnecessary technical language they are valued 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. Our data suggest that any attempt to persuade the public to vaccinate by including technical language in communications designed to explain vaccines is ill advised and that clear, simple, and straightforward information is the best approach to public health information communication.

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