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Disease, perceived infectibility and threat reactivity: a COVID-19 study

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Pre-registration statement

We applied the same analyses as those pre-registered following the collection of the first wave (<https://osf.io/5cexn/>). The results presented in the paper were conducted on the final sample, in other words on the participants who completed both waves. In addition, after the pre-registration, we automatically coded the correspondence between postal codes and upper tier local areas, which corrected issues due to the initial manual coding.

Declaration of interest

None.

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Disease, perceived infectibility and threat reactivity: a COVID-19 study

Abstract

Using a two-wave online experiment, we investigate whether COVID-19 exposure changes participants' threat-detection threshold. Threat reactivity was measured in a signal detection task among 277 British adults who also reported how vulnerable they felt to infectious diseases. Participants' data were then matched to the local number of confirmed COVID-19 cases announced by the NHS every day. We found that participants who perceive themselves as more likely to catch infectious diseases displayed higher threat reactivity in response to increased COVID-19 cases.

Keywords

Threat reactivity; disease vulnerability; pathogen threat; COVID-19; error-management theory

23 **Introduction**

24

25 Having an accurate perception of potential risks and benefits is essential to optimal
26 decision-making. Although all errors should ideally be avoided, some errors are costlier
27 than others. False positives and false negatives indeed have asymmetric consequences
28 for the individual because failing to detect a threat when there is one is more dangerous
29 than believing that there is a threat when there is none (Haselton & Buss, 2000). Given
30 this asymmetry, error-management theory predicts that individuals should be biased to
31 overdetect negative events. In line with this idea, surveys consistently show that people
32 overperceive all kinds of threats, such as crime rates, terrorism or unemployment risk
33 (Gilbert et al., 2016; Lieder et al., 2016).

34

35 To be adaptive however, threat reactivity must be sensitive to individual circumstances,
36 such as physical condition or age (Nettle & Bateson, 2012). For example, people in poor
37 physical condition can escape less easily from threats, which means that for them, more
38 so than for people in better shape, having a lower threat detection threshold is
39 particularly adaptive. In line with this idea, people in poor physical shape are more prone
40 to the auditory looming effect, a bias that helps us get ready to move away from
41 approaching objects by making us hear sounds that are coming towards us as closer than
42 sounds going away from us (Neuhoff et al., 2012). Similarly, individuals who perceive
43 themselves as more sensitive to diseases have stronger reactions to disease cues
44 (Navarrete & Fessler, 2006; Reid et al., 2012); and women who perceive themselves as
45 more vulnerable to sexual coercion tend to stereotype out-group males as more
46 threatening (McDonald et al., 2015)

47

48

49 In addition to these internal factors, readiness to react to threat should also respond to
50 local circumstances. For instance, in a highly threatening environment, individuals should
51 react more readily to threat cues than in an environment with fewer threats (Nettle &
52 Bateson, 2012). In line with this idea, social perception experiments have shown that
53 maltreated children are more likely to over-detect anger in emotionally ambiguous faces
54 (Pollak, 2008).

55

56 In the present paper, we further test this model by analyzing the effect of the COVID-19
57 epidemic on individuals' threat reactivity. Using signal detection theory, we test the
58 hypothesis that being surrounded by more COVID-19 cases, as measured by local COVID-
59 19 prevalence, will increase people's reactivity to threats. More specifically, we predict
60 that this effect is modulated by individuals' perceived vulnerability to infectious diseases,
61 with a larger effect among individuals who perceive themselves as highly vulnerable to
62 diseases.

63

64 In order to test this hypothesis, we assessed subjective vulnerability in a sample of
65 participants who took part in a threat reactivity experiment twice: on March 24th and two
66 weeks later, on April 7th. Local variations of the number of COVID-19 cases allow us to
67 obtain quasi-experimental natural variations of threat exposure. For instance, on March
68 24th, the urban local tier of Wakefield reported only 13 cases, less than the mostly rural
69 area of Wiltshire, which counted almost 3 times more cases. The evolution of the number
70 of COVID-19 cases also varied from one region to the next. For instance, both Hounslow
71 and Essex districts counted around 80 cases on March 24th but Essex district counted 938
72 cases two weeks later while Hounslow district counted only 279 more cases at that date.

73 Similarly, while the district of Merton ranked 21st in the number of cases on Match 24th it
74 fell to the 40th position on April 7th. Conversely, the district of Liverpool jumped from the
75 47th to 17th position in that same time interval. We thus exploited these local variations
76 in order to assess the combined effect of exposure to disease threat and subjective
77 vulnerability to diseases on participants' reactivity to threat.

78

79

80 **Methods**

81

82 *Ethics Statement.* Our study was approved by the local Ethical Committee (CERES
83 n°201659). Each participant received a description of the study and provided their
84 informed consent before starting the experiment. All scripts and raw data are available
85 in the OSF project (<https://osf.io/5cexn/>).

86

87 *Participants.* 352 UK participants recruited on Prolific Academic completed our study
88 twice: once between March 24th at 2PM and March 25th at 2 PM, and a second time
89 between April 7th at 2PM and April 8th at 2PM. The 2PM limit was chosen because daily
90 figures of COVID19 cases are announced by the British government at that time. All
91 participants received compensation for their time (£5 per hour), as well as a variable
92 bonus depending on task performance (£0-0.50). For both waves, all trials with reaction
93 times below 150 ms or above 2,500 ms were excluded. 1 participant was removed for
94 having mean reaction times at ± 3 SD of the mean in the first wave and 4 were excluded
95 in the second wave. 22 participants were then removed for having reaction times outside
96 these ranges on more than 40% of the trials in the first wave and 8 were excluded based
97 on this same criterion in the second wave. In addition, 7 participants were removed for

98 not having provided answers to the “Perceived Infectability and Germ Aversion”
99 questionnaire in the first wave and 27 participants were removed for not having
100 provided answers to the “Perceived Infectability and Germ Aversion” questionnaire in
101 the second wave (Duncan et al., 2009). Finally, 4 participants were excluded for not
102 having provided their date of birth and 2 participants were excluded from not having
103 provided a valid postal code. In total, 75 participants were excluded, which left us with a
104 final sample of 277 participants living in 112 geographical areas (158 Females, mean age:
105 38.43 ± 12.58 s.d. years).

106

107 *Materials.* The task was presented using Qualtrics. Monetary punishments were
108 presented using text (“- 5 pennies”), which represented the true amount that was
109 subtracted from participants’ total bonus payment at the end of the experiment. The
110 punishments were provided in response to incorrect identifications of a line appearing in
111 the center of a circle as being short (11.5mm) or long (13mm). Following the
112 experimental task, participants completed questionnaires including standard socio-
113 demographic questions (age, income, education, postal code of residence) as well as their
114 perceived sensitivity to diseases.

115

116 *Design and Procedure.* The experiment was conducted online and lasted approximately
117 25 minutes. Participants were told that their task was to classify a line as either short or
118 long by pressing the corresponding key and that feedback for incorrect responses would
119 occur some of the time. The training phase consisted of 22 practice trials during which
120 the difficulty of the task was progressively raised until real-game conditions were
121 reached.

122

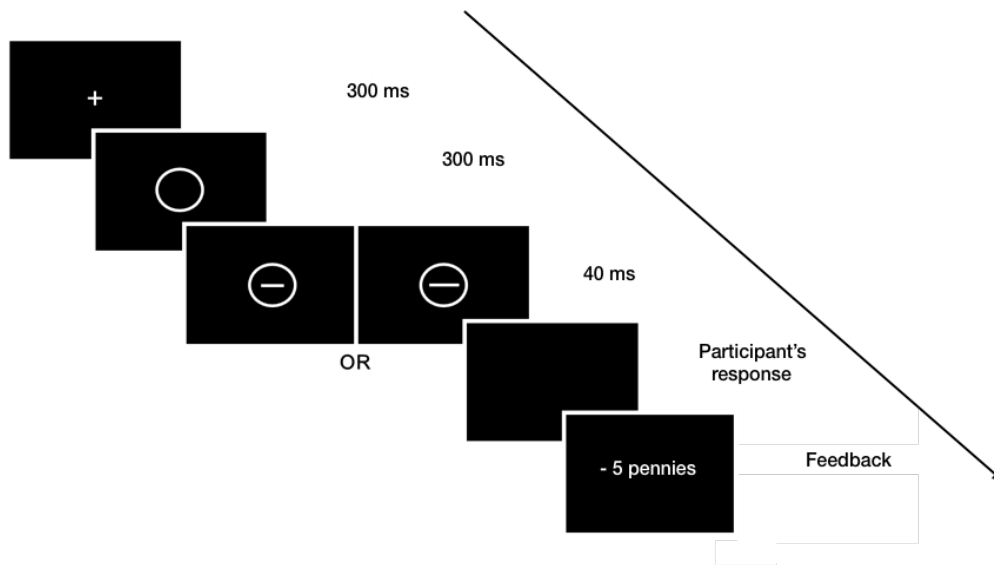
123 The experiment consisted of 300 trials separated in three 100-trial blocks. Each trial
124 began with the presentation of a fixation cross (300ms), followed by an empty circle
125 (300ms). The short or the long line was then flashed within the circle (40ms) and
126 disappeared to show a plain black screen during which participants could submit their
127 response (Figure 1). An equal number of short and long lines were presented within each
128 block. Short and long lines were presented in a random order. Participants were given an
129 infinite amount of time to indicate their response using 'e' or 'p' on the keyboard. Based
130 on the reinforcing schedule, incorrect responses were followed by an 800ms negative
131 feedback screen with a probability of 75% or 25%, depending on the type of stimulus (see
132 below). Otherwise, the next trial was immediately presented.

133

134 An asymmetrical reinforcement ratio was introduced such that one type of line (i.e. short
135 or long) was punished more often. The line type that was punished more frequently is
136 referred to as the "harsh stimulus" and the line type that was punished less frequently is
137 referred to as the "lenient stimulus". Misidentifying the harsh line (i.e., if the harsh line is
138 short, a misidentification is to respond "long") was followed by a negative feedback with
139 a probability of 75%. Misidentifying the lenient line (i.e., if the lenient line is long, a
140 misidentification is to respond "short") was followed by a negative feedback with a
141 probability of 25%. Analyses from a pilot study using the same behavioral task prove
142 that the actual distribution of negative feedbacks corresponds to the anticipated
143 asymmetric ratio design: on average, 76.1% of errors on the Harsh line and 29.4% of
144 errors on the Lenient line were followed by a negative feedback (-5 pennies). These
145 results are consistent across conditions and blocks. 74% of errors on harsh lines and 28%
146 of errors on lenient lines were punished in Block 1; 74% and 30% in Block 2; and 74%
147 and 21% in Block 3 (Safra et al., 2021).

148

149 The long line was randomly assigned to being the harsh or the lenient stimulus for each
150 participant.



151

152 **Figure 1. Schematic representation of the tasks** A fixation cross appears for 300ms, followed by an
153 empty circle. A short or a long line is then flashed inside the circle for 40ms. Participants have an infinite
154 amount of time to respond before they receive a punishment for some of their incorrect responses.

155

156 *Threat reactivity.* Threat reactivity was conceptualized as participants' bias to avoid
157 punishment. In our task this meant over-detecting the line for which misidentification
158 was associated with more frequent punishment (i.e., the harsh line). Response bias
159 towards the harsh line was computed using the standard signal detection measure:

160

$$161 \quad \text{Log}(b) = \frac{1}{2} \times \text{Log} \left(\frac{\text{Harsh}_{correct} * \text{Lenient}_{incorrect}}{\text{Harsh}_{incorrect} * \text{Lenient}_{correct}} \right)$$

162

163

164 with $\text{Harsh}_{correct}$ and $\text{Lenient}_{correct}$ correspond to the proportion of correct identifications
165 (hits and correct rejections) to the total number of harsh and lenient trials respectively,

166 and *Harsh_{incorrect}* and *Lenient_{incorrect}* correspond to the proportion of false identifications
167 (misses and incorrect rejections) to the total number of harsh and lenient trials
168 respectively. When accuracy was equal to 1 or 0, we followed the log linear correction
169 procedure described by Hautus (1995).

170

171 Following Pizzagalli et al. (2005) and Chevallier et al. (2016), reactivity to threat was
172 computed by measuring the change in bias towards the harsh line between the first block
173 (in which the participant is naive about the value of the two lines) and the last block (in
174 which the participant has experienced that the misidentification of one line is more
175 frequently associated with punishments).

176

177 *Perceived infectability.* At the end of the experiment, participants' susceptibility to
178 infectious diseases was assessed using the "Perceived Vulnerability to Disease"
179 questionnaire (Duncan, Schaller & Park, 2009). This questionnaire is composed of two
180 subscales: the "Perceived Infectability" subscale which measures the self-reported
181 susceptibility to infectious diseases, and the "Germ Aversion" subscale which assess the
182 level of affective responses to situations of high risk of disease transmission. In our study,
183 we used "Perceived Infectability" as our measure of interest as it indicates how much the
184 individual feels threatened by infectious diseases, while "Germ Aversion" was used as a
185 control measure for general affective reactions to diseases.

186 Participants completed these scales twice, once in Wave 1 and a second time in Wave 2.
187 Our data shows strong consistency in participants' response to the perceived
188 vulnerability to disease questionnaire. We found a strong inter-temporal correlation
189 between the two waves for the global disgust score ($r = 0.86 \pm 0.01$ s.e.m., $p < .001$),

190 the perceived infectability score ($r = 0.86 \pm 0.01$ s.e.m., $p < .001$) and the germ aversion
191 score ($r = 0.84 \pm 0.02$ s.e.m., $p < .001$).

192 *Socio-demographic information.* In Wave 1, participants provided information about their
193 age, gender and level of education. Additional questionnaires were also included at the
194 end of Wave 1 and Wave 2 (see Supplementary information for details).

195 *Local COVID-19 exposure.* The number of local COVID-19 cases was retrieved from the
196 NHS website based on participants' postal codes. For residents of England, we retrieved
197 COVID-19 cases statistics at the upper tier local authority level (UTLA) from the NHS
198 website. UTLAs are an administrative subdivision below the level of the region. For
199 residents of Scotland, COVID-19 figures were given at the level of health board areas from
200 the Scotland NHS website (there are 14 such areas). Finally, COVID-19 cases statistics for
201 Wales and Northern Ireland were not available for smaller subdivisions. We thus
202 considered Wales and Northern Ireland as just other administrative sub-divisions.

203

204 Importantly, perceived vulnerability to pathogens was not significantly correlated with
205 the local numbers of COVID-19 cases neither in Wave 1 ($r = .01 \pm 0.06$ s.e.m., $t(275) =$
206 0.13 , $p > .250$) nor in Wave 2 ($r = -.01 \pm 0.06$ s.e.m., $t(275) = -0.21$, $p > .250$). Similarly, in
207 both Waves, no significant correlation was found between the local number of COVID-19
208 cases and the subscales of Perceived Vulnerability to Disease: perceived infectability
209 (Wave 1: $r = -.02 \pm 0.06$ s.e.m., $t(275) = -0.37$, $p > .250$; Wave 2: $r = -.04 \pm 0.06$ s.e.m., $t(275)$
210 $= -0.59$, $p > .250$) and germ aversion (Wave 1: $r = .03 \pm 0.06$ s.e.m., $t(275) = 0.52$, $p > .250$;
211 Wave 2: $r = .02 \pm 0.06$ s.e.m., $t(275) = 0.26$, $p > .250$).

212

213 *Analyses.*

214 Threat reactivity in Wave 1 and in Wave 2 were first analyzed using robust mixed linear
215 regressions taking the number of reported COVID-19 cases in the upper tier local
216 authority, germ aversion and perceived infectability, as well as the interaction between
217 local exposure to COVID-19 and these two dimensions of perceived vulnerability to
218 diseases as predictors. All the predictors were transformed into z-scores to avoid issues
219 due to scaling differences. To control for individual and local effects independent of the
220 exposure to COVID-19 (such as living in a rural area or in a city), participant ID and the
221 upper tier local authority was included as a random factor. In order to further assess the
222 robustness of our results, we conducted additional models with age, gender and level of
223 education as additional predictors.

224

225 Finally, in order to compare participants' behavior across the two waves, we analysed
226 Waves 1 and 2 simultaneously using similar robust mixed linear regressions as
227 previously but taking "Wave" as additional predictor. All the robust mixed linear
228 regressions were conducted using *robustlmm* R package (Koller, 2016).

229

230 **Results**

231 No main effect of COVID-19 exposure was found on threat reactivity ($b = -0.07 \pm 0.06$
232 s.e.m., $z = -1.24$, $p = .215$). However, there was a significant positive effect of the
233 interaction between exposure to COVID-19 and perceived infectability ($b = 0.15, \pm 0.07$
234 s.e.m., $z = 2.27$, $p = .023$) such that participants who perceived themselves as more likely
235 to catch infectious diseases reacted more strongly to the number of COVID-19 cases in
236 their surroundings (Table 1). This effect was robust to the inclusion of age, gender and
237 level of education (interaction between perceived infectability and COVID-19 exposure:
238 $b = 0.18 \pm 0.07$ s.e.m., $z = 2.48$, $p = .013$; no other significant effect, see Table 1) and was

239 specific to perceived infectability as there was no significant effect of germ aversion
240 (main effect: $b = 0.08 \pm 0.06$ s.e.m., $z = 1.31$, $p = .190$; interaction: $b = -0.00 \pm 0.05$ s.e.m.,
241 $z = -0.01$, $p > .250$).

242 Analysis of Waves 1 and 2 confirmed the positive interaction between exposure to COVID-
243 19 and perceived infectability ($b = 0.10 \pm 0.05$ s.e.m., $z = 2.22$, $p = .026$; Table 1). This
244 effect was still found as a trend after including demographic variables as predictors ($b =$
245 0.10 ± 0.05 s.e.m., $z = 1.85$, $p = .064$; Table 1).

246 To sum up, differences in the number of COVID-19 cases had no overall effect on
247 participants' threat reactivity but participants with a high sensitivity to diseases had a
248 lower threat reactivity threshold when they lived in an area with many COVID-19 cases
249 than when those who lived in an area with few COVID-19 cases. This suggests that threat
250 reactivity increased in response to higher levels of disease threat among those who
251 perceived themselves as vulnerable to diseases.

252 One possible interpretation of our findings is that participants with a higher perceived
253 sensitivity to diseases are also those who are more informed. We ruled out this possibility
254 by measuring participants' accuracy when estimating the number of COVID-19 cases in
255 the UK. We found that perceived infectability was not correlated with participants'
256 accuracy when they estimated the number of COVID-19 cases in the UK ($r = 0.04 \pm 0.06$
257 s.e.m., $t(275) = 0.66$, $p > .250$; non-signed error: $r = -0.04$, $t(275) = -0.63 \pm 0.06$ s.e.m.,
258 , $p > .250$; measured in Wave 2) and that the interaction between the number of COVID-
259 19 cases and perceived infectability remained significant after adjusting for participants'
260 knowledge of the epidemics (after controlling for signed error: $b = 0.09 \pm 0.05$ s.e.m., $z =$
261 1.97 , $p = .049$; after controlling for non-signed error: $b = 0.09 \pm 0.05$ s.e.m., $z = 1.89$, $p =$
262 $.058$). This suggests that participants with a high level of perceived infectability do not

263 have a better or a more catastrophic image of the situation than those with a low level of
264 perceived infectability.

	Wave 1		Waves 1 & 2	
	Reduced model	Full model	Reduced model	Full model
Intercept	0.23 ± 0.06 *** z = 4.09	0.28 ± 0.08 *** z = 3.70	0.21 ± 0.06 *** z = 3.49	0.27 ± 0.07 *** z = 3.77
COVID-19 published cases	-0.07 ± 0.06 z = -1.24	-0.09 ± 0.09 z = -0.96	-0.05 ± 0.05 z = -1.05	-0.04 ± 0.07 z = -0.54
Perceived infectability	Main effect			
	-0.09 ± 0.06 z = -1.63	-0.10 ± 0.06 z = -1.66	-0.05 ± 0.04 z = -1.25	-0.06 ± 0.04 z = -1.53
	Interaction with COVID-19 published cases			
	0.15 ± 0.07 * z = 2.27	0.18 ± 0.07 * z = 2.48	0.10 ± 0.05 * z = 2.22	0.10 ± 0.06 ° z = 1.85
Germ aversion	Main effect			
	0.08 ± 0.06 z = 1.48	0.08 ± 0.06 z = 1.31	0.06 ± 0.04 z = 1.48	0.06 ± 0.04 z = 1.47
	Interaction with COVID-19 published cases			
	1.01 ± 0.05 z = 0.17	-0.00 ± 0.05 z = -0.01	-0.04 ± 0.03 z = -1.30	-0.05 ± 0.03 z = -1.39
Age	Main effect			
		-0.02 ± 0.06 z = -0.36		0.04 ± 0.04 z = 1.10
	Interaction with the number of COVID-19 published cases			
		-0.05 ± 0.08 z = -0.63		-0.04 ± 0.05 z = -0.72
Gender	Main effect			
		-0.12 ± 0.12 z = -1.06		-0.12 ± 0.08 z = -1.49
	Interaction with the number of COVID-19 published cases			
		0.05 ± 0.12 z = 0.43		-0.00 ± 0.09 z = -0.02
Education level	Main effect			
		1.01 ± 0.06 z = 0.18		-0.01 ± 0.04 z = -0.15
	Interaction with the number of COVID-19 published cases			
		-0.07 ± 0.08 z = -0.86		-0.04 ± 0.05 z = -0.72
Wave			-0.01 ± 0.09 z = -0.09	-0.03 ± 0.09 z = -0.36

266 **Table 1. Coefficients of the mixed linear regression on threat reactivity conducted on Wave 1 alone and Waves**
267 **1 and 2 simultaneously.** A positive interaction was found between perceived infectability and the number of COVID-
268 19 published cases in the local area. Standardized regression coefficients are presented with the standard error to
269 mean and the associated z value. ° indicates a p-value inferior to .100, * indicates a p-value inferior to .050 and ***
270 indicates a p-value inferior to .001.

271 **Discussion**

272

273 In line with our hypothesis, our results revealed that variations in threat reactivity was
274 associated to a combination of local threat level (as measured by the local prevalence of
275 COVID-19) and individual sensitivity to threat: the more individuals perceived
276 themselves as susceptible to infectious diseases, the more COVID-19 exposure increased
277 their reactivity to threats. This effect was present at the two time-points of the epidemics
278 we had access to: on the day following the official lockdown enforcement in the UK and
279 two weeks later. These results provide evidence that individuals react to the presence of
280 survival threats by decreasing their threshold for responding to punishment (Nettle &
281 Bateson, 2012). These results are in line with previous findings by Makhanova &
282 Shepherd (2020) suggesting that perceived infectability to diseases is associated with
283 increased vigilance to health and disease-related issues in the context of COVID-19
284 pandemic.

285

286 Going further, the present study reveals that psychological adjustments following an
287 increase of threat in the environment acts at the global level of individuals' psychology.
288 More precisely, it appears that disease threat, such as COVID-19 exposure, modulates
289 threat reactivity across domains, even if the threat is not linked to health, as it is the case
290 with the financial punishments used in our experiment.

291

292 Crucially, the significant interaction between perceived infectability and local COVID-19
293 exposure suggests that this response is conditional on the level of perceived threat and
294 not on the absolute level of threat in the environment. Therefore, it appears that this
295 effect is genuinely mediated by individuals' perceived risks and benefits of adopting

296 different strategies in the response to an environmental change. Importantly, this effect
297 was independent from individuals' knowledge of the epidemic as well as their age, gender
298 and level of education.

299

300 In a nutshell, our study provides evidence that individuals react to the presence of threats
301 in their environment by decreasing their threshold for reacting to threats. Moreover, our
302 results show that adaptation of low-level psychological variables is conditional on how
303 much the threat that is present in the environment corresponds to a threat subjectively
304 perceived as such by the individual. This underlines the importance of taking inter-
305 individual differences into account when designing public policies in response to large
306 scale public threats.

307

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