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► To cite this version:

Martin Breyton, Émilien Schultz, A. Smith, Alexandra Rouquette, J. Mancini. Information overload in the context of COVID-19 pandemic: A repeated cross-sectional study. *Patient Education and Counseling*, 2023, 110, 10.1016/j.pec.2023.107672 . hal-04122801

HAL Id: hal-04122801

<https://hal.science/hal-04122801v1>

Submitted on 22 Sep 2023

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1 Information overload in the context of COVID-19 pandemic: a
2 repeated cross-sectional study.

3

4 Martin Breyton^{1,2}, Émilien Schultz^{1,3}, Allan Ben Smith^{4,5}, Alexandra Rouquette^{6,7}, Julien
5 Mancini^{1,8}

6

7 1 - Aix Marseille Univ, INSERM, IRD, ISSPAM, SESSTIM, Cancer, Biomedicine & Society group,
8 Equipe Labellisée Ligue 2019, Marseille, France

9 2 - AP-HM, Marseille, France

10 3 - CEPED (UMR 196), Université de Paris, IRD, 75006 Paris, France

11 4 - Centre for Oncology Education and Research Translation (CONCERT), Ingham Institute for
12 Applied Medical Research & South Western Sydney Clinical School, University of New South
13 Wales, Liverpool, NSW, Australia

14 5 - Psycho-Oncology Co-operative Research Group (PoCoG), School of Psychology, University
15 of Sydney, Australia

16 6 - Public Health and Epidemiology Department, AP-HP Paris-Saclay, Le Kremlin-Bicêtre,
17 France

18 7 - Université Paris-Saclay, UVSQ, CESP, INSERM U1018, Villejuif, France

19 8 - AP-HM, BIOSTIC, Hop Timone, Marseille, France

20

21 **Corresponding author at:**

22 Julien Mancini

23 UMR1252 SESSTIM (Aix-Marseille Univ)

24 Institut Paoli-Calmettes

25 232 Bd Ste Marguerite, BP 156

26 13273 Marseille Cedex 9, FRANCE

27 E-mail: julien.mancini@univ-amu.fr

28 Telephone: +33 4 91 22 35 02

29 Facsimile: +33 4 91 22 35 04

30

31 Abstract

32 **Objectives:** To assess the psychometric properties of the Coronavirus Information Overload
33 scale (CovIO) and explore relationships between CovIO, its predictors and several health
34 behaviours related to the COVID-19 pandemic, using Cancer Information Overload (CIO)
35 scale results as a reference for comparison.

36 **Methods:** 2,003 participants representative of the French adult population answered a self-
37 administered questionnaire over two waves of polling ($N_{1(\text{June } 2020)}=1,003$, $N_{2(\text{January } 2021)}=1,000$). Respondents were randomized to fill CovIO or CIO scale. Psychometric
38 properties of scales were evaluated with Confirmatory Factor Analysis (CFA). Predictors were
39 assessed using multivariate linear regression.
40

41 **Results:** CovIO scale showed satisfactory psychometric properties ($\alpha=0.86$, $\omega=0.86$,
42 $RMSEA=0.050$) without any measurement invariance issue. CovIO increased between waves
43 of sampling and was significantly linked to education, health literacy and trust in institutions
44 among other variables. A negative relationship between information overload and
45 preventive behaviours was also observed.

46 **Conclusion:** The CovIO scale is a valid tool for assessing COVID-19 information overload. The
47 dynamical formation of information overload and links with theorised predictors, especially,
48 health literacy are confirmed.

49 **Practice implications: Longitudinal designs could help better understand the potential**
50 **detrimental effect of information overload and improving public health campaigns.**

51 **Interventions to reduce the degree of overload are needed.**

52

53 **Keywords:** Cancer information overload; Coronavirus information overload; Health literacy;
54 Health behaviour; Validation studies; Psychometrics

55

56 **Highlights:**

- 57 ● The CovIO scale is a valid tool to assess information overload relating to COVID-19
- 58 ● CovIO is linked to socioeconomic predictors but also related to trust in various media
- 59 and health professionals
- 60 ● CovIO translates into negative health behaviours just like CIO does
- 61 ● There is a clear increase in CovIO across the time of the pandemic

62 1 Introduction

63 The COVID-19 pandemic hit the world at a global scale, with unprecedented media coverage.
64 With it came a continuous flow of rapidly changing information: daily numbers of cases and
65 deaths, updates about progression of the outbreak worldwide, promotion of
66 countermeasures, barrier gestures, vaccines, lockdowns, etc. Citizens were asked to follow
67 health recommendations, some of them enforced by law, that rapidly changed and for some
68 of them were disputed in public space: as in France for lockdown or health pass[1].

69 Recent research has investigated the impact of information overload on various chronic
70 disease (e.g. cancer, atrial fibrillation)[2–4]. The COVID-19 pandemic offers an unmatched
71 opportunity to study information overload in the context of an acute disease with a high
72 information environment[5]. In this specific context, the huge amount of information
73 available, the high level of uncertainty regarding its validity, and the frequent spread of
74 misinformation[6] might lead to a very high level of information overload. Previous studies
75 of COVID-19 information[7–9] have not validated a scale to capture COVID-19 information
76 overload (CovIO) and studied its predictors in the same population sample. Existing attempts
77 lacked representativeness or adequate methodological rigour, such as a control group.
78 Furthermore, despite a growing body of evidence on health information overload on
79 different topics, there are still discrepancies concerning key covariates, namely health
80 literacy and education in various studies[4]. Our previous work on Cancer Information
81 Overload (CIO)[10], demonstrated the possibility of valid assessment with a 5-item scale and
82 found an association with poorer health related behaviours. We hypothesise that a similar
83 pattern may occur for CovIO, even if little is known about information overload in the
84 context of such a pandemic. In particular, CovIO might evolve rapidly as the epidemiological
85 and informational context changes. A valid tool to measure CoVIO and identify associated
86 health behaviours is needed to better assess and manage the impact of CoVIO in research
87 and practice.

88 The main objectives of our study were: to validate the psychometric properties of the CovIO
89 scale, to study its predictors, and to explore the relationships between CovIO and several
90 health behaviours over the first year of the COVID-19 pandemic in the general public. The
91 same analyses were performed in parallel with the CIO for comparison.

92

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94
95

96 2 Methods

97 2.1 Samples

98 We used data from large national repeated cross-sectional surveys conducted by IPSOS[11]
99 in the French general adult population[12,13]. Data was collected in two waves, the first
100 between May 27th and June 5th, 2020 (two weeks after the end of the first lockdown), and
101 the second between January 8th and January 18th 2021 (where a curfew was set at 6PM).
102 Participants were selected from an online nationally representative research panel of
103 households of the French general population, and quota sampling was used to match French
104 official census statistics for gender, age, size of the population in the area of residence, and
105 region. At each time of data collection, participants were randomly assigned to receive the
106 CIO scale (CIO group) or its adaptation to capture COVID-19 Information Overload (CovIO
107 group). The study was approved by the Ethics Evaluation Committee of the French national
108 biomedical research Institute (CEEI, IRB 00003888).

109
110

111 2.2 Measures

112 2.2.1 The Information Overload scales

113 The CIO group completed the French version of the 5-item CIO scale (CIO group)[10], while
114 the CovIO group completed an equivalent scale adapted to the context of the pandemic: the
115 Coronavirus Information Overload (CovIO) scale. This adaptation consisted of replacing
116 occurrences of the word “cancer” in the CIO scale with “coronavirus (COVID-19)”. For
117 example, the first item of the CIO scale: *“There are so many different recommendations*
118 *about cancer, it’s hard to know which ones to follow”*, became *“There are so many different*
119 *recommendations about the coronavirus (COVID-19), it’s hard to know which one to follow”*
120 (Table 1). The adaptation used both ‘coronavirus’ and ‘COVID-19’ terms due to the
121 polysemic use of those designations of the disease, and that SARS CoV2 was seldom
122 used[14]. A 4-point Likert scale (strongly disagree = 1, disagree = 2, agree = 3, strongly agree

123 = 4) was used for each item and items were summed to produce a total score for each scale
124 ranging from 5 to 20, with higher scores indicating greater information overload.

125

126 2.2.2 Other measures

127 The questionnaire comprised questions regarding: socio-demographics (age, gender,
128 education, rural or urban living area), chronic comorbidities, the occurrence of COVID-19
129 within the participant's household and level of preoccupation regarding the COVID-19
130 pandemic and its consequences. Health literacy was assessed using the French version of the
131 HLS₁₉-Q12 questionnaire[15]. A score was computed by summing all twelve 4-point items
132 giving a range between 12 and 48, higher score indicating higher health literacy. Health
133 information seeking behaviour was assessed with a question about general health
134 information seeking in any source (books, magazines, internet, social media...). Trust in
135 institutions was measured with four questions regarding journalists, politicians, scientists,
136 and physicians. Finally, we inquired about several health-related behaviours linked to cancer
137 or COVID-19 prevention. For cancer prevention we asked for: the number of days per week
138 of tobacco use, alcohol consumption, physical exercise (more than 30 minutes), and healthy
139 diet. For COVID-19 we asked for the number of unsafe contacts, i.e. the number of social
140 interactions without respecting barrier gestures (excluding people within the household)
141 during the past week (*“None, Only one, Two or three, Between Four and Eight, More than
142 Eight”*).

143

144

145 2.3 Statistical analyses

146 Continuous and categorical variables were described using means (\pm standard deviation) and
147 counts (percentages) respectively. Univariate analyses were performed and significance was
148 measured using chi-square tests, Student t tests or ANOVAs for categorical and continuous
149 variables respectively. Tests were two-sided and the p-values were considered significant
150 when less than 0.05. All the following analyses were conducted for both scales, CovIO and
151 CIO, using R.3.5.2 and RStudio.

152

153 **2.3.1 Score and item responses description**

154 Floor or ceiling effects at the scale level were considered to be present if more than 15% of
155 respondents achieved the lowest or highest possible score, respectively[16]. At the item
156 level, these effects were considered to be present if more than 95% endorsed if the lowest
157 or highest response category[17].

158

159 **2.3.2 Internal consistency and structural validity**

160 Items were considered redundant if the polychoric inter-item correlation > 0.7 and irrelevant
161 if < 0.2 [16]. Reliability was assessed using ordinal Cronbach's alpha (α)[18] and McDonald's
162 Omega (ω)[19], and considered satisfactory if ≥ 0.7 [20].

163 Structural validity was tested using confirmatory factor analysis (CFA) with the robust
164 weighted least squares (WLSMV) estimator and Delta parameterization[21,22]. The initial
165 factor structure explored was the unidimensional structure (as determined by Jensen and
166 colleagues for the CIO scale) and modification indices were then examined, if necessary, to
167 allow correlation between items until fit indices were satisfactory[2]. The following fit
168 indices were used: the Root Mean Square Error of Approximation (indicating a good fit if
169 RMSEA < 0.05 , poor fit if ≥ 0.10 , acceptable elsewhere, the Comparative Fit Index and the
170 Tucker-Lewis index (CFI and TLI, indicating a good fit if > 0.95 , poor fit if < 0.90 , acceptable
171 elsewhere[23]).

172

173 **2.3.3 Measurement invariance**

174 After assessing structural validity, measurement invariance was explored using multiple-
175 group CFA and nested model comparisons. It was consecutively studied over the following
176 variables: *age* (< 50 and ≥ 50 years), *gender*, *education level* (more than high school or not),
177 and the presence or absence of a *chronic condition*. We used the classic three-step sequence
178 investigating configural, metric and scalar invariance consecutively by fitting and testing
179 three different nested models with increasing constraints[21,24]. To explore gender
180 invariance for example, the same model was initially hypothesized for both groups and the
181 following sequence of nested model tests was constructed: 1) configural invariance:
182 unconstrained factor loadings and item thresholds; 2) metric invariance: factor loadings
183 constrained to be equal across gender groups and unconstrained item thresholds; 3) scalar
184 invariance: factor loadings and item thresholds constrained to be equal across gender

185 groups. Each level of invariance was considered to be met if the fit indices difference
186 between two nested models (unconstrained – constrained) was equal or less than 0.01 for
187 ΔCFI and equal or higher than -0.015 for $\Delta RMSEA$ [25,26]. When a level of invariance was not
188 met, non-invariant items were identified by reviewing modification indices (essentially the χ^2
189 value) in order to release equality constraints concerning these items until partial invariance
190 was met.

191

192 2.3.4 CIO and CovIO predictors

193 Candidate variables to be screened as CIO and CovIO predictors were: polling wave, gender,
194 age, education, living area, chronic disease, personal-history of COVID-19, history of COVID-
195 19 within the household, preoccupation with COVID-19, health information seeking
196 behaviour, health literacy, trust in journalists, politics, physicians, and scientists. CovIO and
197 CIO predictors were identified across the two waves using linear regression models stratified
198 with respect to the random assignment to the CovIO (N=1,003) or CIO group (N=1,000). The
199 Akaike Information Criteria[27] and stepwise (forward and backward) methods were used
200 for model selection[28]. Interaction terms between all candidate variables and the *wave*
201 variable were tested using a global F-test comparing models with and without interaction
202 terms. Stepwise regression was then initiated on the model with all candidate variables and,
203 if the global F-test for interaction was significant, all the interaction terms.

204

205 2.3.5 CIO, CovIO and Health behaviours

206 Lastly, relationships between CIO, CovIO and various health related behaviours were
207 investigated by comparing mean levels of overload across several variables. We
208 hypothesized that overload would be systematically associated with detrimental behaviours
209 (e.g. higher levels of CIO would be linked to tobacco use or alcohol consumption, and higher
210 levels of CovIO were expected to be related to higher number of social interactions without
211 barrier gestures in the past week)[10,29]. Every hypothesis was either tested with an ANOVA
212 or Pearson's correlation and considered significant when the p-value was below 0.05.

213

214

215

216

217 3 Results

218 3.1 Samples

219 1,003 participants responded during the first wave of polling and 1,000 during the second. In
220 line with French census statistics, there was an almost equal distribution between men
221 (50.8%) and women (49.2%) in the 2,003 participants who responded to the surveys. The
222 mean age was 46.5 (± 15.6) years old. The population was mostly urban (78.9%) and
223 educated with 1,209 participants (60.4%) with a degree higher than high school graduation.
224 Almost half the participants (44.9%) reported at least one chronic condition. Only 128 (6.4%)
225 respondents indicated having been infected by COVID-19, and 180 (9.0%) reported an
226 infection within the household. Those rates were higher in the second wave of the survey
227 (Appendix 1). Except for COVID-19 related variables, participants of the two waves were
228 similar. CovIO and CIO groups were also similar. CovIO was found to be significantly higher
229 than CIO ($p < 0.01$) in both waves with mean CovIO of 14.1 (± 3.4) and mean CIO of 13.2 (± 3.0).
230 See Appendix 1 for a full description of the samples.

231

232 3.2 Score and item responses description

233 There was no missing data for the CovIO and CIO scales. Item responses and score
234 distributions in the CovIO scale are shown in Figure 1. No floor or ceiling effect was detected
235 at the item level: the highest proportion of response for the lowest and highest response
236 category were respectively 12.7% ($N=127$) for item 4 and 30.1% ($N=301$) for item 5. This was
237 also the case at the scale level with a minimum and a maximum total score reached by 8.6%
238 ($N=86$) and 1.3% ($N=13$) of the sample respectively. Similar results were observed regarding
239 CIO (cf. Figure 1 and Appendix 3).

240

241 3.3 Reliability and Confirmatory Factor Analysis

242 Internal consistency of CovIO was satisfactory with both Cronbach's alpha = 0.86 and
243 McDonald's Omega = 0.86. All inter-item polychoric correlations were between 0.2 and 0.7.
244 The initial Confirmatory Factor Analysis fitted poorly with a RMSEA=0.128, CFI=0.98 and
245 TLI=0.96, and it was necessary to allow for error-correlation between items 2 and 3 to obtain
246 satisfactory results: RMSEA=0.050, CFI=0.99, TLI=0.99. Similar adequate psychometric
247 properties were observed regarding CIO (Appendix 3).

248

249 3.4 Measurement Invariance

250 No measurement invariance issue was found during MGCFA for the CovIO scale across
251 gender, education level, age, and the presence or absence of chronic comorbidity. Similar
252 invariance was observed regarding CIO (Appendix 2).

253

254 3.5 Study of predictors (Table 2)

255 *CovIO*

256 The result of the global F-test for interaction was significant (F-statistic=2.27, $p<0.01$),
257 therefore interaction terms were kept in the stepwise procedure. In the retained model
258 (Table 2), CovIO was found to be significantly increased in wave 2 (beta=5.93, $p<0.01$). The
259 trust in physicians and a history of self-infection by COVID-19 were also significantly
260 associated with higher levels of CovIO (beta=1.08, $p=0.014$ and beta=2.31, $p<0.01$
261 respectively). Significant negative interactions were found between wave and health
262 information seeking and between wave and health literacy (Fig 2). Stratified analysis across
263 waves revealed that the negative effects of health information seeking and of health literacy
264 on CovIO were significant only in wave 2 with beta=-1.51 ($p<0.01$) and beta=-0.10 ($p<0.01$)
265 respectively. Higher age and higher education were globally associated with less CovIO
266 (beta=-0.02, $p=0.006$, and beta=-0.63, $p=0.004$ respectively), and so were the trust in
267 politicians (beta=-1.06, $p<0.01$) and scientists (beta=-1.28, $p<0.01$). Lastly, a negative linear
268 relationship between increasing levels of preoccupation for COVID-19 and CovIO was found
269 (beta=-0.65, $p=0.047$).

270

271 *CIO*

272 The global F-test for interaction was not significant ($p= 0.15$). In the final model (Table 2),
273 higher age, education, and preoccupation with COVID-19 were all linked to lower CIO just
274 like with CovIO. Lastly, health literacy and health information seeking were significantly
275 associated with lower CIO, but independently from the sampling period (Fig 2).

276

277 3.6 Health behaviours (Table 3)

278 Mean CovIO levels increased significantly ($p < 0.001$) and monotonously with the number of
279 unsafe social contacts from a mean of 13.4 (± 3.3) for “no contact”, to 14.8 (± 3.5) for “more
280 than 8 contacts”. When explored between waves, this trend was only significant at wave 2,
281 in January 2021 (Fig 3). Regarding more general health behaviours, CovIO showed a
282 significant negative correlation with healthy dieting ($p < 0.01$), but no relationship with
283 physical exercise, tobacco use and alcohol consumption. CIO was also significantly negatively
284 correlated with healthy dieting and physical exercise ($p = 0.042$), and close-to-significantly
285 correlated with tobacco use ($p = 0.070$) and alcohol intake ($p = 0.067$).

286
287

288 4 Discussion and conclusion

289 4.1 Discussion

290 In this study the CovIO scale was a reliable and valid tool (good internal consistency and
291 structural validity) to measure the degree of information overload related to COVID-19,
292 exhibiting measurement invariance across gender, education level, age, and presence of
293 chronic illness.

294 As expected, with an enormous amount of often changing and not always valid[30] COVID-
295 19-related information being broadcast across all media channels during the study period
296 and specific controversies over treatments (e.g., efficacy of chloroquine[31]), CovIO was
297 higher than CIO and increased over time in our study (when adjusting for CoVID-19 related
298 variables such as personal infection and preoccupation). While CIO was higher in this sample
299 compared to our previous study in 2016[10], it was stable across the two survey waves and
300 this difference may reflect the fact that our previous study recruited a convenience sample
301 of people specifically interested in cancer research and that participants not affected by
302 cancer were found to have higher CIO than cancer patients or caregivers[10]. In contrast to
303 our previous results[10] the present results suggest that exposure to an acute disease such
304 as COVID-19 (through personal infection) increases information overload, however, this
305 relationship tends to decrease over time, despite an increased number of infection. This can
306 be due to the specific uncertainty about this virus and the fact that some of the available
307 information became rapidly obsolete or learning that COVID-19 reinfection was possible.

308 The study of interactions suggests that the relationship between CovIO (and very likely
309 information overload in general) and some of its predictors is not static. Indeed, the effects
310 of health literacy and health information seeking behaviours became significant only during
311 wave 2. These results might suggest that as the amount and complexity of information about
312 the virus increased as the pandemic progressed, that health literacy helps navigate through
313 it, or, that respondents with active interest for health information developed specific
314 expertise to navigate this specific information. Similarly, the interaction between time and
315 health seeking behaviours suggests that this mass information accumulating through the
316 pandemic is also complex and sometimes contradictory (e.g debates around the vaccination
317 in France) and more proactive information seeking reduces the amount of overload. This is
318 in line with our previous study showing less information overload among intense
319 information seekers[10]. As expected from previous results[10,32,33] and in accordance
320 with the negative relationship with health literacy, higher education was also significantly
321 associated with lower information overload. Both education level and health literacy are key
322 factors to consider when developing health related messages and programs.

323

324 This is the first report of age being significantly negatively correlated with information
325 overload[32,34] since its formalization by Jensen et al[2]. Although from a cognitive
326 perspective, this results seems contradictory with the natural decline of cognitive processes
327 and the limited capacity model[35], our samples were relatively young (only 15% over 65
328 years old) and it's likely that older people have more interest in health questions but may
329 also be more accepting of official health messages. Such a positive relationship with official
330 health messages would be consistent with the negative association between trust in
331 politicians and overload and deemed important if not crucial in the context of a pandemic
332 where the trust in public health measures appears to be central. But this encouraging result
333 should be tempered by a the context of low trust in politicians in general (only 16.6%, Table
334 S1), which could reflect the evolving political decisions throughout the pandemic (for
335 example, masks were not deemed necessary by the minister of health of France at the
336 beginning of the pandemic[36]). Changing political decisions may both increase overload and
337 erode trust in politicians. On the other hand, the trust in scientists being associated with less
338 CovIO with a very high rate of trust in scientists (88.2%) underlines the value of clear health
339 messages emanating from the scientific community. This link to trust suggests that overload

340 depends on the way individuals select or reject sources of information as credible. However,
341 the most surprising result was about the trust in physicians being linked to higher CovIO
342 when most of the sample declared trusting their physicians (92.7%, Table S1). One
343 speculative explanation could be that individual physicians were also prone to CovIO due to
344 frequent changing recommendations about isolation protocols, systematic screening
345 protocols for contact cases for example or, more generally, an overall feeling of overload (i.e
346 work overload) about COVID-19 that was sensed by day-to-day patients. Alternatively, this
347 could reveal that people who distrust physicians are engaged in an alternative view of the
348 world with its own set of beliefs which, although false, are firm and less prone to
349 information overload[37] or that people who trust physicians were confronted with
350 conflicting information elsewhere, which caused them to feel overwhelmed.
351 Finally, we've shown that CovIO might translate into health behaviours, just like CIO in
352 previous findings[10]. CovIO was related to risky behaviours such as the increase in the
353 number of unsafe contacts (lacking recommended barrier gestures). This relationship was,
354 again, strongest at wave 2 underpinning the dynamic nature of information overload.
355 Although, the desire to return to a normal life could be a confounding factor not measured
356 in our study that could have interacted with CovIO and the compliance to social distancing.
357 For more general health behaviours, CIO was confirmed to be linked with lower physical
358 activity and less days of healthy diet in the week. The correlations with tobacco use and
359 alcohol consumption were also expected but only close to significance. However, the
360 significant relation between CovIO and non-healthy dieting wasn't expected and lacks any
361 reasonable explanation except for a link to health information overload in general. But
362 overall, these results reinforce the purpose of CovIO, CIO and health information overload in
363 general, in capturing some of the reasons why the general population might not engage in
364 healthy preventive behaviours upon clear health messages.

365

366 The major limitation of our study is that despite a repeated design to study the dynamics of
367 information overload in a pandemic context, the participants in the two samples (in June
368 2020 and January 2021) are not the same. However, the sampling method was similar and
369 both waves had good statistical power with large sample sizes. Moreover, the comparison
370 between the characteristics of the two samples didn't reveal any major difference. The same
371 limitation holds for the comparison between CovIO and CIO but to limit the burden of the

372 questionnaire it was not possible to ask sequentially for CovIO and CIO. The questionnaire
373 randomization compensated this limitation. Another limit would be the important number
374 of interactions between the predictors of CovIO discarded. We chose to focus on the
375 interaction with time since it was the main objective of our study. Exploratory analysis on
376 the data, not presented in the article suggested for example many interactions between
377 health literacy and other variables. These interactions should be addressed in later work
378 using, for instance, structural equation modelling with some meaningful constructs (e.g
379 health literacy, trust in various public actors...) yielding results that take in account
380 interactions without losing interpretability. Finally, the context of COVID-19 was marked by
381 specific national contexts of information, with governmental communication and media
382 debates. Especially for CovIO, a joint analysis with available public information at this time
383 would be useful to contextualise the results.

384

385 4.2 Conclusion

386 We have shown that the CovIO scale is a valid instrument to measure the amount of
387 information saturation relating to COVID-19. The huge amount of often changing or
388 conflicting COVID-19 related information in all media appears to have led to greater CovIO
389 than CIO. The relationship to some of its predictors was better characterized and the
390 dynamic nature of its formation revealed.

391

392 4.3 Practice implications

393 **Even though monitoring COVID-19 information might be less relevant recently given the**
394 **evolution of the pandemic and public awareness, our study sheds light on the dynamics of**
395 **information overload in general. Therefore, longitudinal designs are needed to better**
396 **understand the potential detrimental effect of information overload and improve the**
397 **impact of public health campaigns.** Future work should also consider interventional studies
398 to decrease health information overload on a selected topic (e.g. through educational
399 lectures, or dedicated medical sessions) and validate the effects on behaviours.

400

401

402 **Conflict of interest statement**

403 The authors have no conflicts to declare.

404 **Funding**

405 This work benefited from the support of La Ligue Contre le Cancer through the accreditation
406 (LIGUE 2019) of the CANBIOS team.

407 The sponsors had no role in study design; in the collection, analysis and interpretation of
408 data; in the writing of the report; and in the decision to submit the paper for publication.

409 **Authors' contribution**

410 MB: Conceptualization, Formal analysis, Writing – original draft.

411 JM: Conceptualization, Investigation, Writing – review and editing, Supervision, Project
412 administration, Funding acquisition.

413 ES: Investigation, Writing – review and editing

414 AR: Investigation, Writing – review and editing

415 BS: Investigation, Writing – review and editing

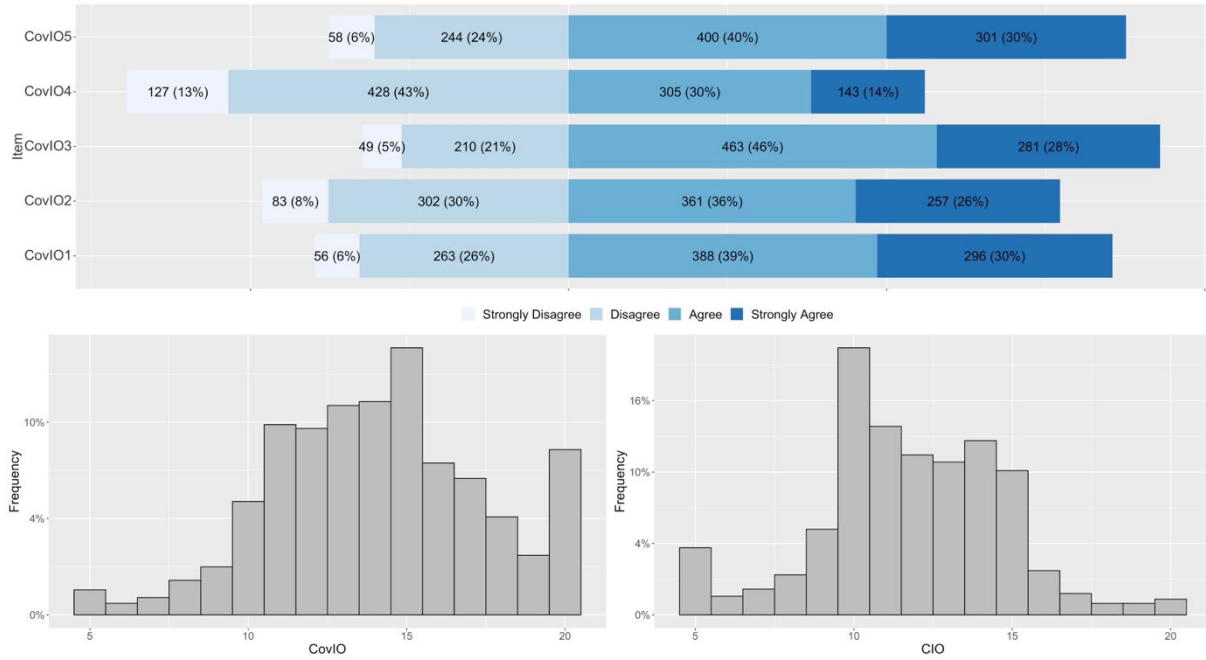
416 **Acknowledgements**

417 We thank the Réseau Francophone de la Littérature en Santé (REFLIS) network for their
418 collaboration in the European HLS₁₉ survey.

419

420 **Figures and Tables**

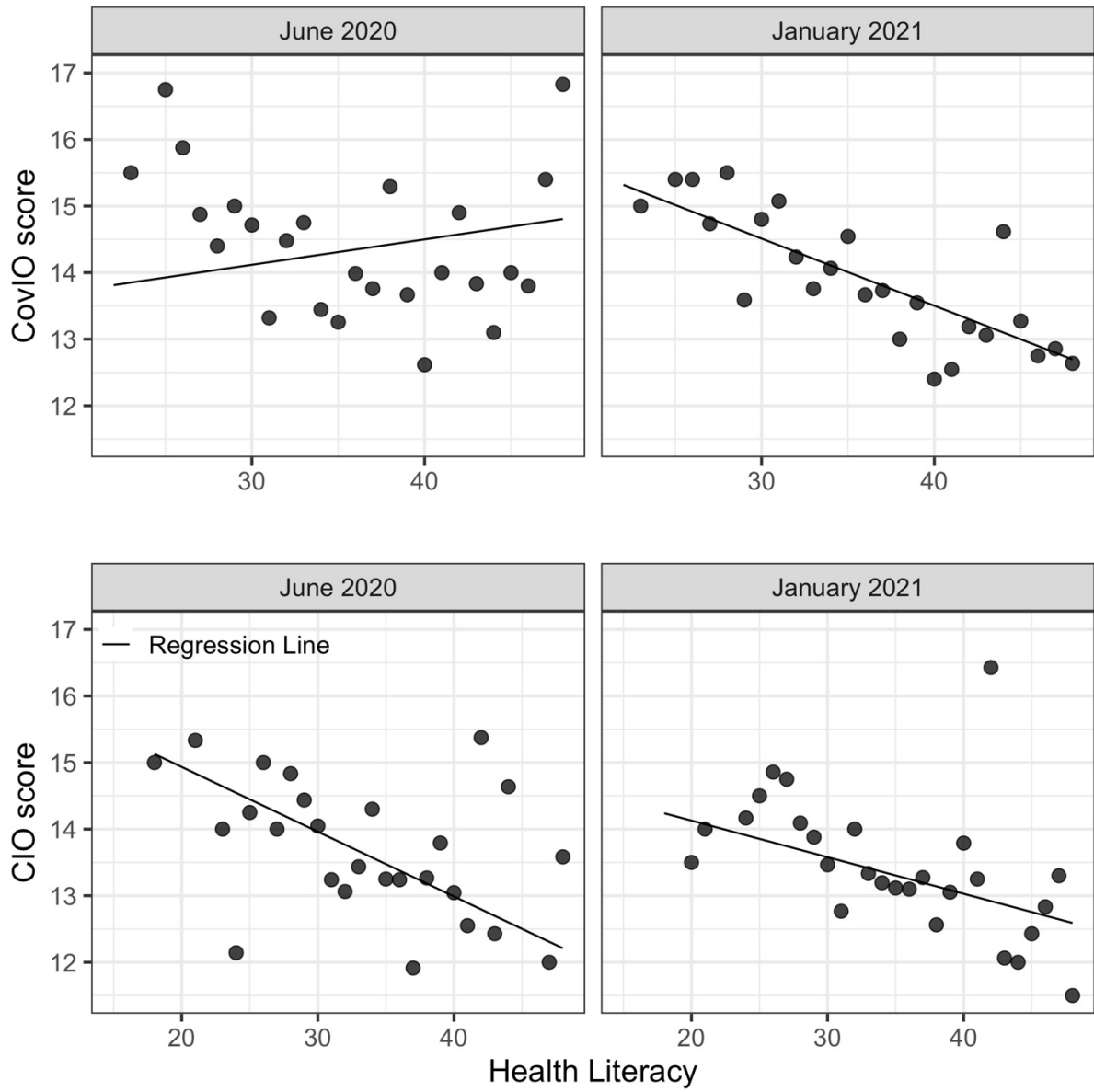
421 **Figure 1: Item responses and score distributions of the COVID-19 Information overload (CovIO) scale**



423

424

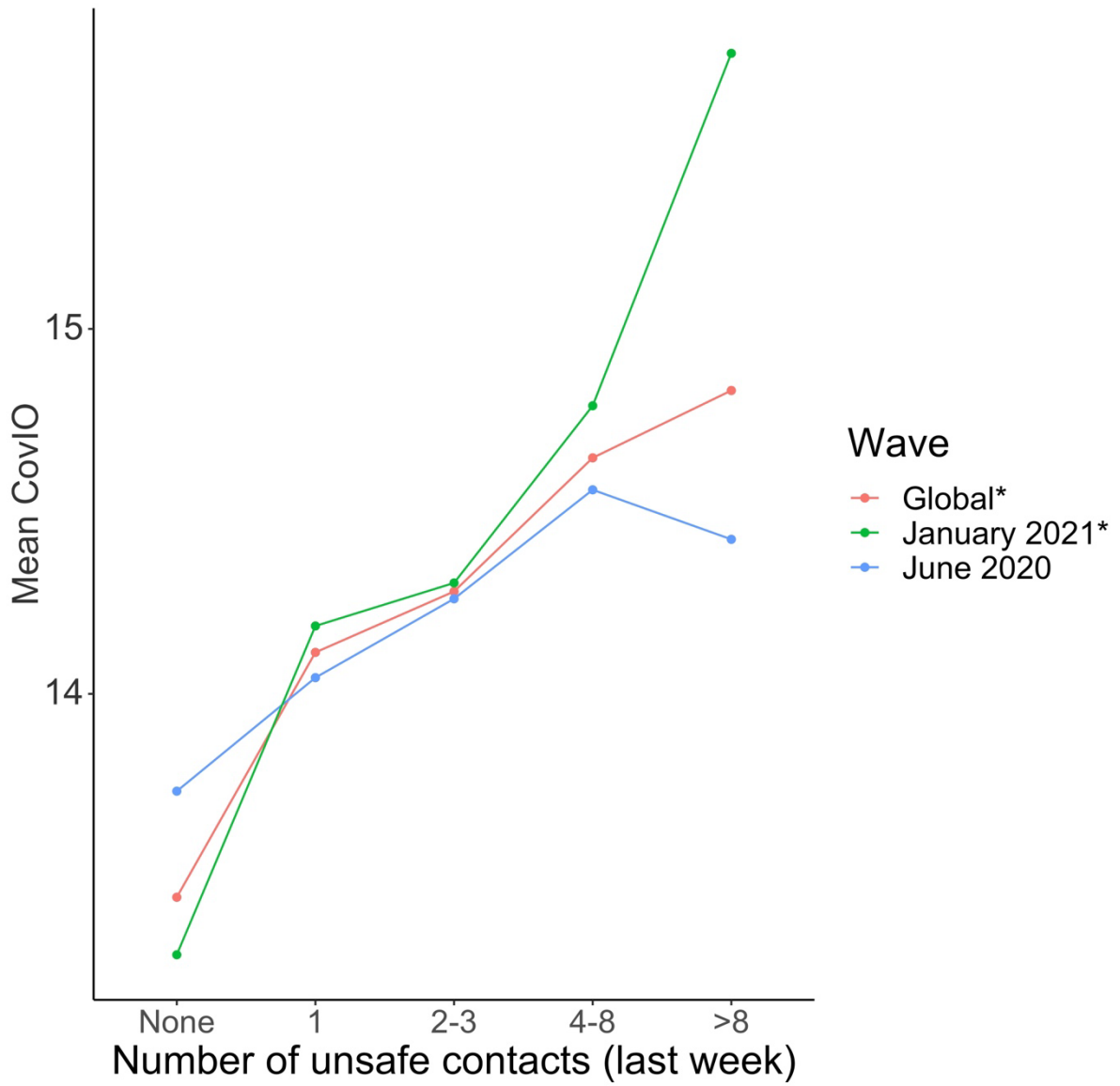
425 Figure 2: Interactions effects of Health Literacy and sampling Wave on CovIO



426

427

428 Figure 3: Univariate link between CovIO and the number of unsafe contacts for the different
429 sampling periods
430



431 *p<0,01

432

433 Table 1: CovIO scale translated from French

	CovIO scale adapted from the CIO scale after Costa <i>et al.</i> 2014 (DOI: 10.1016/j.pec.2015.04.020)	French version
1	There are so many different recommendations about the coronavirus (COVID-19), it's hard to know which ones to follow.	Il y a tellement de recommandations différentes concernant le coronavirus (COVID-19) qu'il est difficile de savoir lesquelles suivre
2	There is so much coronavirus (COVID-19) information, I don't even care to hear new things about coronavirus (COVID-19)	Il y a tellement d'informations sur le coronavirus (COVID-19) qu'en avoir des nouvelles ne m'intéresse même plus
3	There is so much information about coronavirus (COVID-19), it all starts to sound the same after a while.	Il y a tellement d'informations sur le coronavirus (COVID-19), qu'au bout d'un moment elles commencent à toutes se ressembler
4	There is so much coronavirus (COVID-19) information, I forget most coronavirus (COVID-19) information right after I learn it.	Il y a tellement d'informations sur le coronavirus (COVID-19), que j'en oublie la plupart aussitôt après les avoir reçues
5	I feel overloaded by the amount of coronavirus (COVID-19) information I am supposed to know.	Je me sens submergé(e) par la quantité d'informations sur le coronavirus (COVID-19), que je suis censé(e) connaître

434

435 Table 2: Linear regressions of CIO and CovIO on their predictors

	CovIO		CIO	
	β	<i>p</i> -value	β	<i>p</i> -value
(Intercept)	14.62	<0.001	18.46	<0.001
Wave 2 (January 2021)	5.93	<0.001	-	-
Male	0.30	0.159	-	-
Age (per 1-year increase)	-0.02	0.006	-0.02	0.007
Higher Education (> Baccalaureate)	-0.64	0.004	-0.40	0.049
Self-history of COVID-19	2.31	0.001	0.83	0.065
Household-history of COVID-19	-	-	0.63	0.106
Health Information seeking	-0.23	0.585	-1.23	<0.001
Health Literacy (per 1-point increase)	0.04	0.181	-0.08	<0.001
COVID-19 preoccupation (per 1-category increase)	-0.65	0.047	-0.63	0.036
Urban area	-	-	0.39	0.096
Trust in:				
Journalists	0.01	0.973	-	-
Politicians	-1.067	<0.001	-	-
Physicians	1.08	0.014	-0.57	0.123
Scientists	-1.28	<0.001	-	-
Selected interactions:				
Wave 2 * Self-history of COVID-19	-1.47	0.095	-	-
Wave 2 * Health Information seeking	-1.27	0.026	-	-
Wave 2 * Health Literacy	-0.14	<0.001	-	-
Wave 2 * Trust in journalists	-0.81	0.107	-	-

436

437 Table 3: Univariate links between CIO, CovIO and various health behaviours

Response		CovIO	<i>p</i> -value	CIO	<i>p</i> -value
		<i>Mean (SD)</i>		<i>Mean (SD)</i>	
Number of unsafe contacts (within the past week)	None	13.4 (3.3) N=384	<0.001	13.0 (2.9) N=401	0.15
	1	14.1 (3.5) N=88		13.6 (2.9) N=88	
	2-3	14.3 (3.3) N=221		13.3 (2.9) N=221	
	4-8	14.6 (3.1) N=150		13.5 (2.9) N=153	
	>8	14.8 (3.5) N=160		13.5 (3.3) N=137	
Number of days in a typical week with :		<i>r</i> *		<i>r</i>	
Physical activity		-0.039	0.21	-0.064	0.042
Healthy diet		-0.129	<0.01	-0.107	<0.01
Tobacco use		0.048	0.127	0.057	0.070
Alcohol intake		0.019	0.544	0.058	0.067

438 * Pearson's correlation coefficient

439

440 Table S1: Sample characteristics between waves

		Both waves	Wave 1	Wave 2	p-value*
Gender	Female	1017 (50.8)	506 (50.4)	511 (51.1)	<i>0.805</i>
	Male	986 (49.2)	497 (49.6)	489 (48.9)	
Age	Mean (SD)	46.5 (15.6)	46.5 (15.3)	46.5 (15.9)	<i>0.946</i>
Education level	Low**	794 (39.6)	411 (41.0)	383 (38.3)	<i>0.238</i>
	High**	1209 (60.4)	592 (59.0)	617 (61.7)	
Comorbidity	None	1103 (55.1)	538 (53.6)	565 (56.5)	<i>0.214</i>
	At least 1	900 (44.9)	465 (46.4)	435 (43.5)	
Work status	Active	1353 (67.5)	665 (66.3)	688 (68.8)	<i>0.252</i>
	Not active	650 (32.5)	338 (33.7)	312 (31.2)	
Self-history of COVID-19	No	1748 (87.3)	862 (85.9)	886 (88.6)	<i>0.032</i>
	Yes	128 (6.4)	50 (5.0)	78 (7.8)	
	Don't know	127 (6.3)	91 (9.1)	36 (3.6)	
History of COVID-19 within the household	No	1697 (84.7)	851 (84.8)	846 (84.6)	< <i>0.001</i>
	Yes	180 (9.0)	58 (5.8)	122 (12.2)	
	Don't know	126 (6.3)	94 (9.4)	32 (3.2)	
Living area	Rural	423 (21.1)	212 (21.1)	211 (21.1)	<i>0.999</i>
	Urban	1580 (78.9)	791 (78.9)	789 (78.9)	
Health information seeking behavior	No	296 (14.8)	136 (13.6)	160 (16.0)	<i>0.14</i>
	Yes	1707 (85.2)	867 (86.4)	840 (84.0)	
Health Literacy	Mean (SD)	35.7 (5.6)	36.0 (5.6)	35.4 (5.6)	<i>0.009</i>
Do you trust:					
Journalists	No	1476 (73.7)	744 (74.2)	732 (73.2)	<i>0.656</i>
	Yes	527 (26.3)	259 (25.8)	268 (26.8)	
Politicians	No	1671 (83.4)	824 (82.2)	847 (84.7)	<i>0.141</i>
	Yes	332 (16.6)	179 (17.8)	153 (15.3)	
Physicians	No	147 (7.3)	68 (6.8)	79 (7.9)	<i>0.381</i>
	Yes	1856 (92.7)	935 (93.2)	921 (92.1)	
Scientists	No	236 (11.8)	106 (10.6)	130 (13.0)	<i>0.106</i>
	Yes	1767 (88.2)	897 (89.4)	870 (87.0)	
Preoccupation for COVID-19 and its consequences	Not at all	114 (5.7)	53 (5.3)	61 (6.1)	<i>0.018</i>
	A little	461 (23.0)	255 (25.4)	206 (20.6)	
	Somewhat	847 (42.3)	429 (42.8)	418 (41.8)	
	A lot	581 (29.0)	266 (26.5)	315 (31.5)	
CIO score	Mean (SD)	13.2 (3.0)	13.3 (3.1)	13.2 (2.9)	<i>0.865</i>
CovIO score	Mean (SD)	14.1 (3.4)	14.2 (3.2)	14.0 (3.5)	<i>0.329</i>

*Test across waves, **High = degree higher than the Baccalaureate, ***Students, military

CIO: Cancer Information Overload; CovIO: Coronavirus Information Overload

441
442
443

444 Table S2: Group characteristics

		CIO-group	CovIO-group	p-value*
Gender	Female	497 (49.7)	520 (51.8)	0.36
	Male	503 (50.3)	483 (48.2)	
Age	Mean (SD)	46.4 (15.6)	46.6 (15.5)	0.773
Education level	Low**	373 (37.3)	421 (42.0)	0.036
	High**	627 (62.7)	582 (58.0)	
Comorbidity	None	551 (55.1)	552 (55.0)	0.999
	At least 1	449 (44.9)	451 (45.0)	
Work status	Active	687 (68.7)	666 (66.4)	0.293
	Not active	313 (31.3)	337 (33.6)	
Self-history of COVID-19	No	870 (87.0)	878 (87.5)	0.711
	Yes	61 (6.1)	67 (6.7)	
	Missing	69 (6.9)	58 (5.8)	
History of COVID-19 within the household	No	849 (84.9)	848 (84.5)	0.436
	Yes	84 (8.4)	96 (9.6)	
	Missing	67 (6.7)	59 (5.9)	
Living area	Rural	208 (20.8)	215 (21.4)	0.769
	Urban	792 (79.2)	788 (78.6)	
Health information seeking behavior	No	134 (13.4)	162 (16.2)	0.095
	Yes	866 (86.6)	841 (83.8)	
Health Literacy	Mean (SD)	35.9 (5.7)	35.5 (5.5)	0.165
Do you trust:				
Journalists	No	729 (72.9)	747 (74.5)	0.453
	Yes	271 (27.1)	256 (25.5)	
Politicians	No	850 (85.0)	821 (81.9)	0.067
	Yes	150 (15.0)	182 (18.1)	
Physicians	No	73 (7.3)	74 (7.4)	0.999
	Yes	927 (92.7)	929 (92.6)	
Scientists	No	121 (12.1)	115 (11.5)	0.711
	Yes	879 (87.9)	888 (88.5)	
Preoccupation for COVID-19 and its consequences	Not at all	54 (5.4)	60 (6.0)	0.579
	A little	219 (21.9)	242 (24.1)	
	Somewhat	433 (43.3)	414 (41.3)	
	A lot	294 (29.4)	287 (28.6)	
CIO score	Mean (SD)	13.2 (3.0)	-	-
CovIO score	Mean (SD)	-	14.1 (3.4)	-

445 *Test across waves, **High = degree higher than the Baccalaureate, ***Students, military
 446 CIO: Cancer Information Overload; CovIO: Coronavirus Information Overload

447

448 Table S3: Measurement invariance across age groups, education levels, and deprivation, for Cancer Information Overload scale (CIO)

AGE				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.997	.060 (.032-.091)		
M2: Metric**	.997	.059 (.035-.085)	.000 (ΔM1-M2)	.001 (ΔM1-M2)
M3: Scalar***	.995	.055 (.037-.074)	.002 (ΔM2-M3)	.004 (ΔM2-M3)
GENDER				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.999	.036 (.000-.070)		
M2: Metric**	.999	.028 (.000-.059)	.000 (ΔM1-M2)	.008 (ΔM1-M2)
M3: Scalar***	.999	.012 (.000-.016)	.000 (ΔM2-M3)	.012 (ΔM2-M3)
CHRONIC ILLNESS				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.998	.052 (.020-.082)		
M2: Metric**	.997	.059 (.035-.085)	.001 (ΔM1-M2)	-.008 (ΔM1-M2)
M3: Scalar***	.999	.022 (.000-.046)	-.002 (ΔM2-M3)	-.037 (ΔM2-M3)
EDUCATION				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.997	.066 (.038-.096)		
M2: Metric**	.997	.057 (.032-.083)	.000 (ΔM1-M2)	.008 (ΔM1-M2)
M3: Scalar***	.995	.051 (.032-.070)	.001 (ΔM2-M3)	.006 (ΔM2-M3)
* same factor structure across groups				
** loadings constrained to be equal across groups				
***loadings and thresholds constrained to be equal across groups				

449

450 Table S4: Measurement invariance across age groups, education levels, and deprivation, for Coronavirus Information Overload scale (CoviO)

AGE				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.996	.069 (.042-.099)		
M2: Metric**	.996	.059 (.035-.085)	.000 (ΔM1-M2)	.01 (ΔM1-M2)
M3: Scalar***	.991	.063 (.045-.081)	.005 (ΔM2-M3)	-.004 (ΔM2-M3)
GENDER				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.994	.082 (.055-.111)		
M2: Metric**	.995	.065 (.042-.091)	-.001 (ΔM1-M2)	.017 (ΔM1-M2)
M3: Scalar***	.990	.062 (.045-.081)	.005 (ΔM2-M3)	.003 (ΔM2-M3)
CHRONIC ILLNESS				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.997	.055 (.025-.086)		
M2: Metric**	.995	.063 (.04-.089)	.002 (ΔM1-M2)	-.008 (ΔM1-M2)
M3: Scalar***	.991	.061 (.043-.079)	.004 (ΔM2-M3)	.002 (ΔM2-M3)
EDUCATION				
Measurement Invariance model	CFI	RMSEA (90% CI)	ΔCFI	ΔRMSEA
M1: Configural*	.997	.058 (.029-.088)		
M2: Metric**	.997	.055 (.029-.081)	.000 (ΔM1-M2)	.003 (ΔM1-M2)
M3: Scalar***	.994	.05 (.031-.069)	.003 (ΔM2-M3)	.005 (ΔM2-M3)
* same factor structure across groups				
** loadings constrained to be equal across groups				
***loadings and thresholds constrained to be equal across groups				

451

452 Table S5: CFA results for the CovIO and CIO scales

		CovIO scale (N=1003)	CIO scale (N=1000)
Internal consistency	Cronbach's alpha	0.86	0.87
	McDonald's omega	0.86	0.88
Structural validity	RMSEA	0.050 (0.024-0.080)*	0.045 (0.017-0.075)*
	CFI	0.998	0.999
	TLI	0.994	0.997

453 *RMSEA = Root Mean Error of Approximation (95% confidence interval), CFI = Comparative Fit*
 454 *Index, TLI = Tucker-Lewis Index, *With correlation between item 2 and 3*

455

456 Table S6: Polychoric correlations for the CovIO scale

	COVIO1	COVIO2	COVIO3	COVIO4	COVIO5
COVIO1	1				
COVIO2	0.47	1			
COVIO3	0.38	0.63	1		
COVIO4	0.53	0.61	0.56	1	
COVIO5	0.56	0.59	0.54	0.66	1

457

458 Tables S7: Polychoric correlations for the CIO scale

	CIO1	CIO2	CIO3	CIO4	CIO5
CIO1	1				
CIO2	0.41	1			
CIO3	0.45	0.69	1		
CIO4	0.49	0.66	0.64	1	
CIO5	0.52	0.62	0.61	0.74	1

459

460 Table S8. Item responses for the CIO scale (N=1000)

	Strongly Disagree	Disagree	Agree	Strongly Agree
CIO1	24 (2.4%)	186 (18.6%)	566 (56.6%)	224 (22.4%)
CIO2	95 (9.5%)	486 (48.6%)	325 (32.5%)	94 (9.4%)
CIO3	53 (5.3%)	367 (36.7%)	466 (46.6%)	114 (11.4%)
CIO4	60 (6%)	374 (37.4%)	453 (45.3%)	113 (11.3%)
CIO5	78 (7.8%)	376 (37.6%)	432 (43.2%)	114 (11.4%)

461

462

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