



## Information overload in the context of COVID-19 pandemic: A repeated cross-sectional study

Martin Breyton, Émilien Schultz, A. Smith, Alexandra Rouquette, J. Mancini

### ► 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

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

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

Martin Breyton<sup>1,2</sup>, Émilien Schultz<sup>1,3</sup>, Allan Ben Smith<sup>4,5</sup>, Alexandra Rouquette<sup>6,7</sup>, Julien Mancini<sup>1,8</sup>

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

2 - AP-HM, Marseille, France

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

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

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

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

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

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

**Corresponding author at:**

Julien Mancini

UMR1252 SESSTIM (Aix-Marseille Univ)

Institut Paoli-Calmettes

232 Bd Ste Marguerite, BP 156

13273 Marseille Cedex 9, FRANCE

E-mail: [julien.mancini@univ-amu.fr](mailto:julien.mancini@univ-amu.fr)

Telephone: +33 4 91 22 35 02

Facsimile: +33 4 91 22 35 04

## Abstract

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

**Methods:** 2,003 participants representative of the French adult population answered a self-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 properties of scales were evaluated with Confirmatory Factor Analysis (CFA). Predictors were assessed using multivariate linear regression.

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

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

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

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

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

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

## 1 Introduction

The COVID-19 pandemic hit the world at a global scale, with unprecedented media coverage. With it came a continuous flow of rapidly changing information: daily numbers of cases and deaths, updates about progression of the outbreak worldwide, promotion of countermeasures, barrier gestures, vaccines, lockdowns, etc. Citizens were asked to follow health recommendations, some of them enforced by law, that rapidly changed and for some of them were disputed in public space: as in France for lockdown or health pass[1]. Recent research has investigated the impact of information overload on various chronic disease (e.g. cancer, atrial fibrillation)[2–4]. The COVID-19 pandemic offers an unmatched opportunity to study information overload in the context of an acute disease with a high information environment[5]. In this specific context, the huge amount of information available, the high level of uncertainty regarding its validity, and the frequent spread of misinformation[6] might lead to a very high level of information overload. Previous studies of COVID-19 information[7–9] have not validated a scale to capture COVID-19 information overload (CovIO) and studied its predictors in the same population sample. Existing attempts lacked representativeness or adequate methodological rigour, such as a control group. Furthermore, despite a growing body of evidence on health information overload on different topics, there are still discrepancies concerning key covariates, namely health literacy and education in various studies[4]. Our previous work on Cancer Information Overload (CIO)[10], demonstrated the possibility of valid assessment with a 5-item scale and found an association with poorer health related behaviours. We hypothesise that a similar pattern may occur for CovIO, even if little is known about information overload in the context of such a pandemic. In particular, CovIO might evolve rapidly as the epidemiological and informational context changes. A valid tool to measure CoVIO and identify associated health behaviours is needed to better assess and manage the impact of CoVIO in research and practice.

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

## 2 Methods

### 2.1 Samples

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

### 2.2 Measures

#### 2.2.1 The Information Overload scales

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

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

### 2.2.2 Other measures

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

## 2.3 Statistical analyses

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

### 2.3.1 Score and item responses description

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

### 2.3.2 Internal consistency and structural validity

Items were considered redundant if the polychoric inter-item correlation  $> 0.7$  and irrelevant if  $< 0.2$ [16]. Reliability was assessed using ordinal Cronbach's alpha ( $\alpha$ )[18] and McDonald's Omega ( $\omega$ )[19], and considered satisfactory if  $\geq 0.7$ [20].

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

### 2.3.3 Measurement invariance

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

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

#### 2.3.4 CIO and CovIO predictors

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

#### 2.3.5 CIO, CovIO and Health behaviours

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

## 3 Results

### 3.1 Samples

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

### 3.2 Score and item responses description

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

### 3.3 Reliability and Confirmatory Factor Analysis

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

### 3.4 Measurement Invariance

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

### 3.5 Study of predictors (Table 2)

#### *CovIO*

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

#### *CIO*

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

### 3.6 Health behaviours (Table 3)

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

## 4 Discussion and conclusion

### 4.1 Discussion

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

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

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

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

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

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

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

## 4.2 Conclusion

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

## 4.3 Practice implications

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

## 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

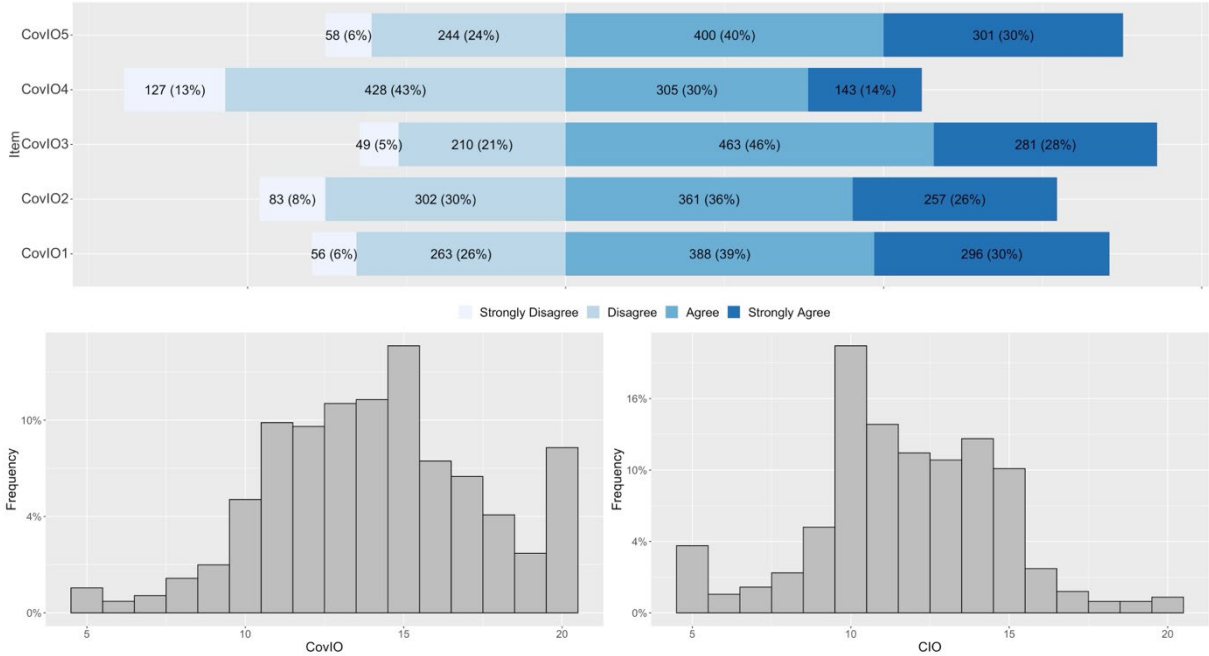
#### 416 **Acknowledgements**

417 We thank the Réseau Francophone de la Littérature en Santé (REFLIS) network for their  
418 collaboration in the European HLS<sub>19</sub> survey.

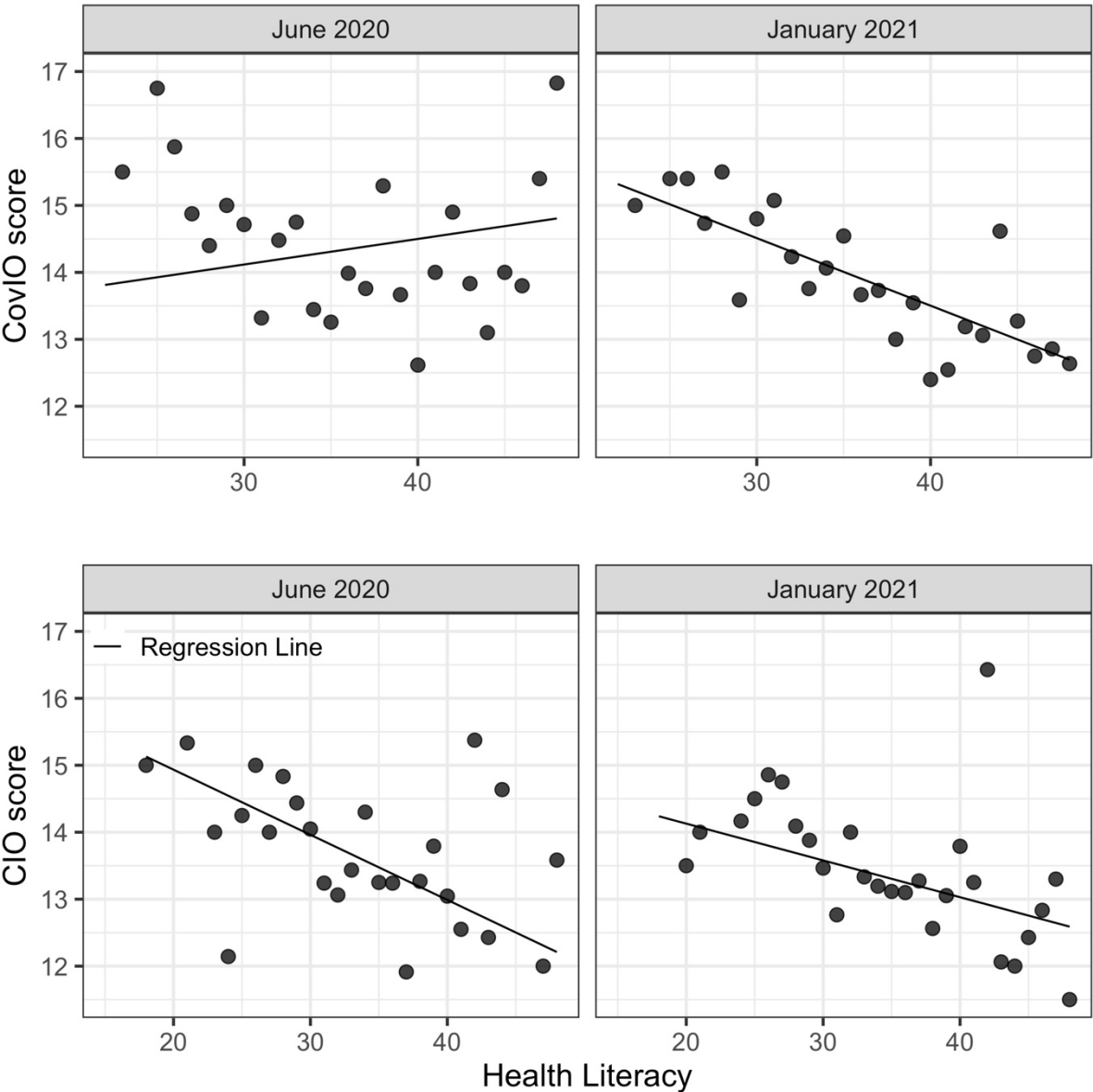
419

Figures and Tables

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



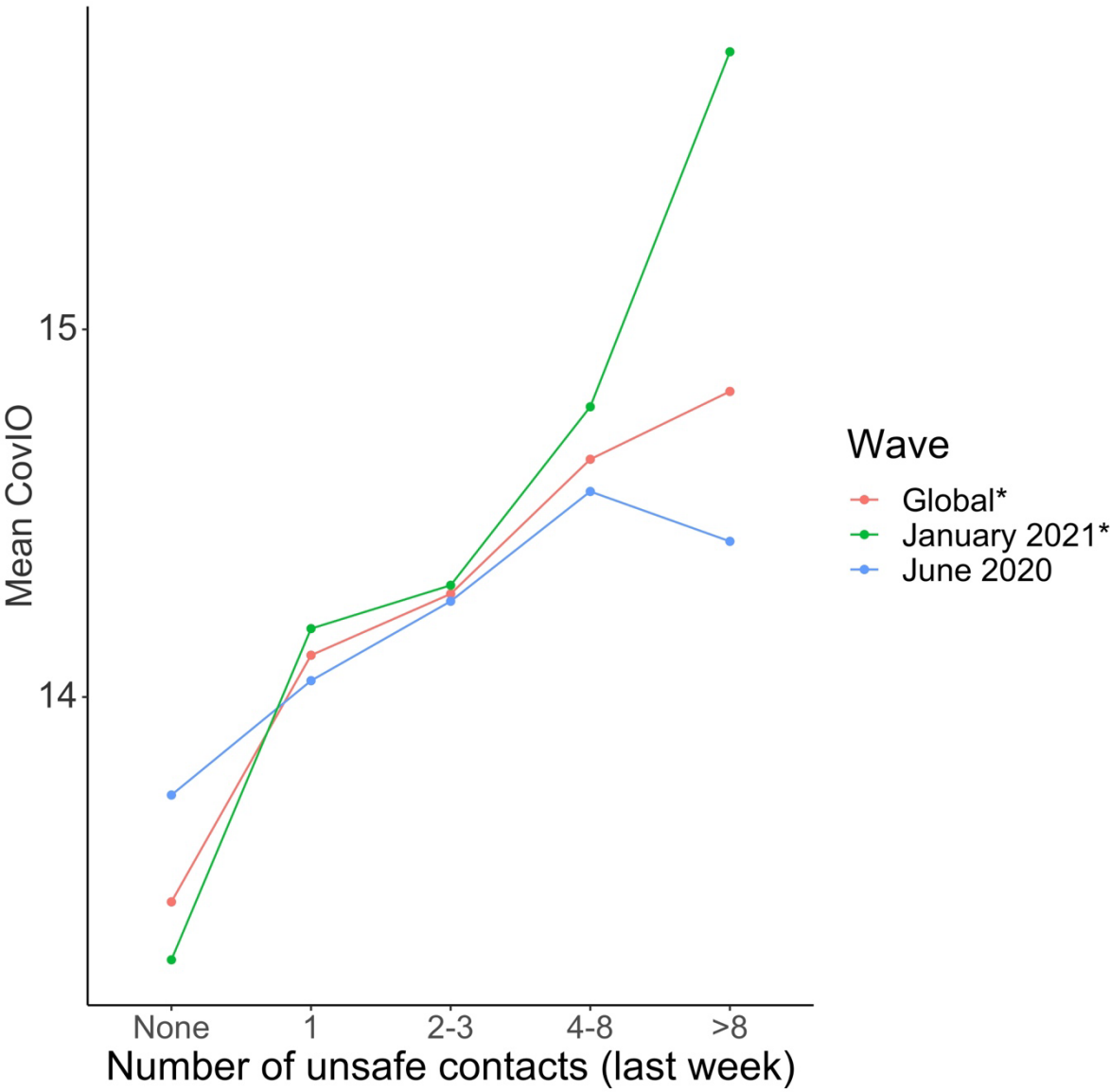
425 Figure 2: Interactions effects of Health Literacy and sampling Wave on CovIO



426

427

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



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

436

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

Response		CovIO	<i>p-value</i>	CIO	<i>p-value</i>
		<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>

441 \*Test across waves, \*\*High = degree higher than the Baccalaureate, \*\*\*Students, military  
442 CIO: Cancer Information Overload; CovIO: Coronavirus Information Overload  
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)

<b>AGE</b>				
Measurement Invariance model	CFI	RMSEA (90% CI)	$\Delta$ CFI	$\Delta$ RMSEA
<b>M1: Configural*</b>	.997	.060 (.032-.091)		
<b>M2: Metric**</b>	.997	.059 (.035-.085)	.000 ( $\Delta$ M1-M2)	.001 ( $\Delta$ M1-M2)
<b>M3: Scalar***</b>	.995	.055 (.037-.074)	.002 ( $\Delta$ M2-M3)	.004 ( $\Delta$ M2-M3)
<b>GENDER</b>				
Measurement Invariance model	CFI	RMSEA (90% CI)	$\Delta$ CFI	$\Delta$ RMSEA
<b>M1: Configural*</b>	.999	.036 (.000-.070)		
<b>M2: Metric**</b>	.999	.028 (.000-.059)	.000 ( $\Delta$ M1-M2)	.008 ( $\Delta$ M1-M2)
<b>M3: Scalar***</b>	.999	.012 (.000-.016)	.000 ( $\Delta$ M2-M3)	.012 ( $\Delta$ M2-M3)
<b>CHRONIC ILLNESS</b>				
Measurement Invariance model	CFI	RMSEA (90% CI)	$\Delta$ CFI	$\Delta$ RMSEA
<b>M1: Configural*</b>	.998	.052 (.020-.082)		
<b>M2: Metric**</b>	.997	.059 (.035-.085)	.001 ( $\Delta$ M1-M2)	-.008 ( $\Delta$ M1-M2)
<b>M3: Scalar***</b>	.999	.022 (.000-.046)	-.002 ( $\Delta$ M2-M3)	-.037 ( $\Delta$ M2-M3)
<b>EDUCATION</b>				
Measurement Invariance model	CFI	RMSEA (90% CI)	$\Delta$ CFI	$\Delta$ RMSEA
<b>M1: Configural*</b>	.997	.066 (.038-.096)		
<b>M2: Metric**</b>	.997	.057 (.032-.083)	.000 ( $\Delta$ M1-M2)	.008 ( $\Delta$ M1-M2)
<b>M3: Scalar***</b>	.995	.051 (.032-.070)	.001 ( $\Delta$ M2-M3)	.006 ( $\Delta$ M2-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)	$\Delta$ CFI	$\Delta$ RMSEA
M1: Configural*	.996	.069 (.042-.099)		
M2: Metric**	.996	.059 (.035-.085)	.000 ( $\Delta$ M1-M2)	.01 ( $\Delta$ M1-M2)
M3: Scalar***	.991	.063 (.045-.081)	.005 ( $\Delta$ M2-M3)	-.004 ( $\Delta$ M2-M3)
GENDER				
Measurement Invariance model	CFI	RMSEA (90% CI)	$\Delta$ CFI	$\Delta$ RMSEA
M1: Configural*	.994	.082 (.055-.111)		
M2: Metric**	.995	.065 (.042-.091)	-.001 ( $\Delta$ M1-M2)	.017 ( $\Delta$ M1-M2)
M3: Scalar***	.990	.062 (.045-.081)	.005 ( $\Delta$ M2-M3)	.003 ( $\Delta$ M2-M3)
CHRONIC ILLNESS				
Measurement Invariance model	CFI	RMSEA (90% CI)	$\Delta$ CFI	$\Delta$ RMSEA
M1: Configural*	.997	.055 (.025-.086)		
M2: Metric**	.995	.063 (.04-.089)	.002 ( $\Delta$ M1-M2)	-.008 ( $\Delta$ M1-M2)
M3: Scalar***	.991	.061 (.043-.079)	.004 ( $\Delta$ M2-M3)	.002 ( $\Delta$ M2-M3)
EDUCATION				
Measurement Invariance model	CFI	RMSEA (90% CI)	$\Delta$ CFI	$\Delta$ RMSEA
M1: Configural*	.997	.058 (.029-.088)		
M2: Metric**	.997	.055 (.029-.081)	.000 ( $\Delta$ M1-M2)	.003 ( $\Delta$ M1-M2)
M3: Scalar***	.994	.05 (.031-.069)	.003 ( $\Delta$ M2-M3)	.005 ( $\Delta$ M2-M3)
* same factor structure across groups				
** loadings constrained to be equal across groups				
***loadings and thresholds constrained to be equal across groups				

451

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

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

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

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

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%)

## 463   References

- 464   [1]   Ward JK, Gauna F, Gagneux-Brunon A, Botelho-Nevers E, Cracowski J-L, Khouri C, et al.  
465       The French health pass holds lessons for mandatory COVID-19 vaccination. *Nat Med*  
466       2022;28:232–5. <https://doi.org/10.1038/s41591-021-01661-7>.
- 467   [2]   Jensen JD, Carcioppolo N, King AJ, Scherr CL, Jones CL, Niederdeppe J. The cancer  
468       information overload (CIO) scale: Establishing predictive and discriminant validity.  
469       *Patient Educ Couns* 2014;94:90–6. <https://doi.org/10.1016/j.pec.2013.09.016>.
- 470   [3]   Obamiro K, Lee K. Information overload in patients with atrial fibrillation: Can the  
471       cancer information overload (CIO) scale be used? *Patient Educ Couns* 2019;102:550–4.  
472       <https://doi.org/10.1016/j.pec.2018.10.005>.
- 473   [4]   Khaleel I, Wimmer BC, Peterson GM, Zaidi STR, Roehrer E, Cummings E, et al. Health  
474       information overload among health consumers: A scoping review. *Patient Educ Couns*  
475       2019. <https://doi.org/10.1016/j.pec.2019.08.008>.
- 476   [5]   Valika TS, Maurrasse SE, Reichert L. A Second Pandemic? Perspective on Information  
477       Overload in the COVID-19 Era. *Otolaryngol Neck Surg* 2020;163:931–3.  
478       <https://doi.org/10.1177/0194599820935850>.
- 479   [6]   World Health Organization. Coronavirus disease 2019 (COVID-19): situation report, 86.  
480       World Health Organization; 2020.
- 481   [7]   Sarkhel S, Bakhla AK, Praharaj SK, Ghosal MK. Information overload regarding COVID-  
482       19: Adaptation and validation of the cancer information overload scale. *Indian J*  
483       *Psychiatry* 2020;62:481–7.  
484       [https://doi.org/10.4103/psychiatry.IndianJPsychiatry\\_974\\_20](https://doi.org/10.4103/psychiatry.IndianJPsychiatry_974_20).
- 485   [8]   Mohammed M, Sha’aban A, Jatau AI, Yunusa I, Isa AM, Wada AS, et al. Assessment of  
486       COVID-19 Information Overload Among the General Public. *J Racial Ethn Health*  
487       Disparities 2021. <https://doi.org/10.1007/s40615-020-00942-0>.
- 488   [9]   Hong H, Kim HJ. Antecedents and Consequences of Information Overload in the COVID-  
489       19 Pandemic. *Int J Environ Res Public Health* 2020;17:9305.  
490       <https://doi.org/10.3390/ijerph17249305>.
- 491   [10]   Breyton M, Smith AB, Rouquette A, Mancini J. Cancer information overload: Association  
492       between a brief version of the CIO scale and multiple cancer risk management  
493       behaviours. *Patient Educ Couns* 2020. <https://doi.org/10.1016/j.pec.2020.09.016>.
- 494   [11]   Ipsos | Bienvenue sur notre site n.d. <https://www.ipsos.com/fr-fr> (accessed March 4,  
495       2021).
- 496   [12]   Touzani R, Schultz E, Holmes SM, Vandentorren S, Arwidson P, Guillemin F, et al. Early  
497       Acceptability of a Mobile App for Contact Tracing During the COVID-19 Pandemic in  
498       France: National Web-Based Survey. *JMIR MHealth UHealth* 2021;9:e27768.  
499       <https://doi.org/10.2196/27768>.
- 500   [13]   Schultz É, Ward JK, Atlani-Duault L, Holmes SM, Mancini J. French Public Familiarity and  
501       Attitudes toward Clinical Research during the COVID-19 Pandemic. *Int J Environ Res*  
502       *Public Health* 2021;18:2611. <https://doi.org/10.3390/ijerph18052611>.
- 503   [14]   Naming the coronavirus disease (COVID-19) and the virus that causes it n.d.  
504       [https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-](https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it)  
505       [guidance/naming-the-coronavirus-disease-\(covid-2019\)-and-the-virus-that-causes-it](https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it)  
506       (accessed February 2, 2022).
- 507   [15]   The HLS19 Consortium of the WHO Action Network M-POHL (2021): International  
508       Report on the Methodology, Results, and Recommendations of the European Health

- Literacy Population Survey 2019-2021 (HLS19) of M-POHL. Austrian National Public Health Institute, Vienna n.d. [https://m-pohl.net/sites/m-pohl.net/files/inline-files/HLS19\\_International%20Report%20%28002%29\\_0.pdf](https://m-pohl.net/sites/m-pohl.net/files/inline-files/HLS19_International%20Report%20%28002%29_0.pdf) (accessed January 17, 2022).
- [16] Terwee CB, Bot SDM, de Boer MR, van der Windt DAWM, Knol DL, Dekker J, et al. Quality criteria were proposed for measurement properties of health status questionnaires. *J Clin Epidemiol* 2007;60:34–42. <https://doi.org/10.1016/j.jclinepi.2006.03.012>.
- [17] Vet HCW de, Terwee CB, Mokkink LB, Knol DL. *Measurement in Medicine* by Henrica C. W. de Vet. *Camb Core* 2011. <https://doi.org/10.1017/CBO9780511996214>.
- [18] Gadermann AM, Guhn M, Zumbo BD. Estimating ordinal reliability for Likert-type and ordinal item response data: A conceptual, empirical, and practical guide n.d.;17:13.
- [19] McDonald RP. *Test theory: a unified treatment*. Mahwah, N.J: L. Erlbaum Associates; 1999.
- [20] Bland JM, Altman DG. Statistics notes: Cronbach’s alpha. *BMJ* 1997;314:572. <https://doi.org/10.1136/bmj.314.7080.572>.
- [21] Brown TA. *Confirmatory factor analysis for applied research*. Second edition. New York ; London: The Guilford Press; 2015.
- [22] Muthen LK, Muthen B. *Mplus user’s guide: statistical analysis with latent variables, user’s guide*. 2017.
- [23] Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct Equ Model Multidiscip J* 1999;6:1–55. <https://doi.org/10.1080/10705519909540118>.
- [24] Kline RB. *Principles and Practice of Structural Equation Modeling* n.d.:554.
- [25] Chen FF. Sensitivity of Goodness of Fit Indexes to Lack of Measurement Invariance. *Struct Equ Model Multidiscip J* 2007;14:464–504. <https://doi.org/10.1080/10705510701301834>.
- [26] Cheung GW, Rensvold RB. Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance. *Struct Equ Model Multidiscip J* 2002;9:233–55. [https://doi.org/10.1207/S15328007SEM0902\\_5](https://doi.org/10.1207/S15328007SEM0902_5).
- [27] Akaike H. A new look at the statistical model identification. *IEEE Trans Autom Control* 1974;19:716–23. <https://doi.org/10.1109/TAC.1974.1100705>.
- [28] Zhang Z. Variable selection with stepwise and best subset approaches. *Ann Transl Med* 2016;4:136. <https://doi.org/10.21037/atm.2016.03.35>.
- [29] Jensen JD, Pokharel M, Carcioppolo N, Upshaw S, John KK, Katz RA. Cancer information overload: Discriminant validity and relationship to sun safe behaviors. *Patient Educ Couns* 2019. <https://doi.org/10.1016/j.pec.2019.08.039>.
- [30] Orso D, Federici N, Copetti R, Vetrugno L, Bove T. Infodemic and the spread of fake news in the COVID-19-era. *Eur J Emerg Med* 2020;10.1097/MEJ.0000000000000713. <https://doi.org/10.1097/MEJ.0000000000000713>.
- [31] Schultz É, Atlani-Duault L, Peretti-Watel P, Ward JK. Does the public know when a scientific controversy is over? Public perceptions of hydroxychloroquine in France between April 2020 and June 2021. *Therapies* 2022;S0040595722000105. <https://doi.org/10.1016/j.therap.2022.01.008>.
- [32] Chae J, Lee C, Jensen JD. Correlates of Cancer Information Overload: Focusing on Individual Ability and Motivation. *Health Commun* 2016;31:626–34. <https://doi.org/10.1080/10410236.2014.986026>.

- [33] Chan YM, Huang H. Weight Management Information Overload Challenges in 2007 HINTS: Socioeconomic, Health Status and Behaviors Correlates. *J Consum Health Internet* 2013;17:151–67. <https://doi.org/10.1080/15398285.2013.780540>.
- [34] Kyunghye Kim, Lustria MLA, Burke D, Kwon, Nahyun. Predictors of cancer information overload. *Inf Reasearch* 2007;12.
- [35] Lang A. The Limited Capacity Model of Mediated Message Processing. *J Commun* 2000;50:46–70. <https://doi.org/10.1111/j.1460-2466.2000.tb02833.x>.
- [36] Déclaration de M. Olivier Véran, ministre des solidarités et de la santé et de Mme Agnès Pannier-Runacher, secrétaire d’État auprès du ministre de l’économie et des finances, en réponse à une question sur la gestion des stocks de masques, à l’Assemblée. *Vie Publique*fr n.d. <https://www.vie-publique.fr/discours/274863-olivier-veran-20052020-gestion-des-stocks-de-masques> (accessed November 29, 2021).
- [37] Attwell K, Ward PR, Meyer SB, Rokkas PJ, Leask J. “Do-it-yourself”: Vaccine rejection and complementary and alternative medicine (CAM). *Soc Sci Med* 2018;196:106–14. <https://doi.org/10.1016/j.socscimed.2017.11.022>.