



The COVID-19 Preventive Behaviors Index: Development and Validation in Two Samples From the United Kingdom

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Abstract

Monitoring compliance with, and understanding the factors affecting, COVID-19 preventive behaviors requires a robust index of the level of subjective likelihood that the individual will engage in key COVID-19 preventive behaviors. In this article, the psychometric properties of the COVID-19 Preventive Behaviors Index (CPBI), including its development and validation in two samples in the United Kingdom, are described. Exploratory and confirmatory factor analyses were performed on data from 470 participants in the United Kingdom who provided demographic information and completed the Fear of COVID-19 Scale, the COVID-19 Own Risk Appraisal Scale (CORAS) and the CPBI. Results showed that a unidimensional, 10-item model fits the data well, with satisfactory fit indices, internal consistency and high item loadings onto the factor. The CPBI correlated positively with both fear and perceived risk of COVID-19, suggesting good concurrent validity. The CPBI is a measure of the likelihood of engaging in preventive activity, rather than one of intention or actual action. It is adaptable enough to be used over time as a monitoring instrument by policy makers and a modeling tool by researchers.

Keywords

COVID-19 Preventive Behaviors Index, perceived risk, fear of COVID-19, prevention, scale validation

Introduction

This paper describes the development, validation and psychometric properties of the COVID-19 Preventive Behaviors Index. The rapid, global spread of SARS-CoV-2, since its identification in China in December 2019, has led to international efforts to contain and curb the virus and COVID-19, the disease it creates. While efforts to develop effective treatment and vaccines have proceeded, control of the disease has rested upon changing the behavior patterns of people to limit opportunities for the transmission of the virus. This would depend on whether people would comply with preventive behavior rules and guidance (Ferguson et al., 2020). Monitoring compliance and understanding the factors affecting it have become a prime target for social science research during the pandemic (Plohl & Musli, 2020). This effort relies on having valid and reliable measures of preventive behaviors. The COVID-19 Preventive Behaviors Index (CPBI) described here was developed for this purpose.

Behavior Change Requirements

COVID-19 is a respiratory disease and the virus is spread primarily via small droplets from coughing, sneezing, and talking. At the outbreak of the pandemic, the routes of transmission were uncertain but, once the primary means of spreading the virus were established, the task was to identify which behaviors

needed to be changed in order to restrict the routes and rate of transmission.

Behavioral change efforts varied considerably internationally and throughout the outbreak. Governments differed in how quickly they introduced guidance or regulations to control behavior; in the severity of the constraints they imposed; in the length of time these were applied; and in the policies that they adopted to support people in making the changes needed. The UK government, rather than immediately adopting stringent social distancing, initially encouraged the most vulnerable individuals to self-isolate (“shield”) and others to continue normally—possibly hoping to build “herd immunity” (Fontanet & Cauchemez, 2020). However, in March 2020 an extensive lockdown across England was introduced.

Despite national variations in strategies there were important commonalities reflected in the slogan “Wear a mask, wash your hands and keep a safe distance.” Individuals were to protect themselves and others by their own actions. Originally,

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there were two primary components of the guidance. First, follow strict hygiene principles—e.g. in the US, wash hands often, with soap, for at least 20 seconds; cover your mouth and nose (not with your hands) when you cough or sneeze; and put used tissues in a waste bin immediately. Second, stay “socially distant,” that is, avoid close contact with anyone you do not live with. In the UK, this was translated into staying at least 2 meters away from anyone from outside your own household or “support bubble.” Allowable composition of “bubbles” was dictated by government or institutional policies. Another form of distancing, largely directed at those most vulnerable, entailed strict self-isolation. One measure introduced bridged hygiene and social distancing: wearing a face mask. The value of face masks as prophylactics was only slowly accepted. The WHO (2020) announced in June 2020 that the public should wear masks, not just to protect the wearer but, as significantly, to protect others from being infected by the wearer. One other behavioral change was required once mass testing for the virus and tracking contacts was viable. People were asked to get tested if they suspected they had symptoms or had been in contact with someone infected and also to allow their contacts to be monitored. The CPBI was developed to create a measure that would reflect these four common elements of preventive behavior guidance and regulations that apply across many countries. In light of the importance of the public remaining updated on the guidance that was being given, it includes an item concerning likelihood of information seeking. While the CPBI was developed in the UK, its items are designed, with very limited adaptation according to context, to be useable internationally.

Compliance and Compulsion

The preventive behaviors described above are essentially actions of the individual and are reliant on individual choices. Amid COVID-19, such choices were made alongside imposed societal-level changes. In the UK, these included the closure of schools and higher education institutions; compulsory shifts to homeworking for many jobs; cessation of mass attendance events; closure of some retail outlets and restriction of access to others; and requirement to quarantine. These measures constituted “lockdown.” Such constraint of public freedom of movement and association was unprecedented in the UK in peacetime and triggered protest against the lockdown (Gayle et al., 2020).

During lockdown, insofar as individuals were socially isolated, compulsion supplanted compliance with preventive guidance. Once lockdown began to be eased, greater freedoms were returned. Workplaces, shops, restaurants, and bars were open again, and willingness to comply with preventive precautions at the individual level emerged as a vital issue (Lopez & Rodo, 2020). After lockdown measures were eased in July, a resurgence of infections occurred during August and September. This onset of “the second wave” of COVID-19 (reflected in a growth rate for infections of 4%–8% per day by 25th September, Gov.UK, 2020) suggested that individual level

compliance alone would not contain the disease. Consequently, compulsory lockdown measures were re-introduced. These included making some previously voluntary behavior compulsory, with fines for failure to comply and policing of compliance.

As behavior moves status from compliance to compulsion, individual choices about taking preventive action acquire a different meaning. This difference has to be acknowledged when measuring the likelihood of someone engaging in preventive behavior. Additionally, as guidance and rules change and become more complex during a pandemic, failure to adopt the appropriate preventive behavior may have less to do with non-compliance than to do with confusion (Breakwell & Jaspal, 2020; Geldsetzer, 2020). Conspiracy theories and misinformation (Allington et al., 2020) and the proliferation of competing social representations of infection and transmission risks and methods of protection have fueled confusion (Jaspal & Nerlich, 2020). How far people think they are likely to take some preventive action will depend in part on both their reaction to compulsion and to confusion.

Developing a Valid and Reliable Measure of COVID-19 Preventive Behaviors

Difficulties emerge when trying to construct a useful measure of COVID-19 preventive behaviors. Most obviously, the preventive behaviors that people are asked to adopt change over time and vary across locations. Moreover, the desirability of compliance with particular behaviors differs across categories of people—for instance, by age, employment and COVID-19 vulnerability (Daoust, 2020). Identity concerns, such as the pursuit of self-esteem, continuity, self-efficacy and distinctiveness, also impinge on behavior (Breakwell, 2015; Murtagh et al., 2012). Furthermore, as public health guidance changes and previous restrictions are lifted, any measure of preventive behaviors will need to be adapted to the novel social and political context. Designing a measure that works over time and across people entails trading off specificity for generalizability.

Many studies have examined preventive behaviors. They vary widely in the measures of preventive behavior they report. Some include items derived directly from government guidelines (Park et al., 2020; Toussaint et al., 2020; Vally, 2020). Others adapt measurement scales used in previous epidemics. For instance, Yıldırım and Guler (2020) adapted a scale developed for use in a SARS outbreak (Brug et al., 2004). Others focus on only one or two behaviors (e.g. mask wearing or hand washing). Given that preventive behaviors are measured in so many different ways, it is difficult to compare findings across studies.

Rare studies (e.g. Yang et al., 2020) have used observational and longitudinal methods; most have relied upon self-report measures. The form of the questions varies markedly even when the behavior targeted is identical. Notably, some ask about intentions and some about actual behavior. Some ask about past behavior, some about current behavior. Some asked about the probability (likelihood) that the behavior will be

adopted, others allow only a definitive yes/no response. Occasionally, the question requires an ancillary response, e.g. whether they intend to do the behavior and whether they expect to actually do it (Hernández-Padilla et al., 2020). Clearly, the use of a considerable variety of response categories also makes comparison across studies problematic.

It would be valuable to have a standard COVID-19 preventive behavior index that is amenable to being used over the course of the pandemic in different contexts. This would help systematic monitoring but would also facilitate modeling factors influencing changes in behavior. Given the commonalities across prevention guidelines and policies that have emerged, the measure would need to index: social distancing behaviors, hygiene behaviors, social isolation behaviors, and test and track behaviors. It should also extend to assessing whether people are likely to seek to keep themselves up to date on the latest advice available about prevention of the virus spread so that they remain aware of what they should be doing. Over time, the formulation of items within each of these categories would need updating as policies or medical knowledge change but the categories themselves are unlikely to change—with one exception: a new category concerning acceptance of COVID-19 vaccination would be required. It may be premature to include it yet since there is no vaccine available. Answers about vaccination would have a different standing to those about other preventive behaviors since, unlike them, vaccination is currently not available. The measure whose development is reported here is designed to offer a standard index of preventive behaviors in the first four categories plus willingness to seek COVID-19 information.

The measure is not aimed at being an index specifically of compliance with health protection guidelines operating at any one time. It focusses upon self-reported likelihood of doing certain behaviors that fall into the four categories identified plus the issue of remaining informed. The individual's motives for their actions are not assessed. Individuals are asked to forecast their behavior (taking into consideration the various subjective factors that may influence it) rather than to explain it. The explanation could be a desire to be compliant but it could equally be habit, ignorance, social conformity, or several other things. Explanations are not conflated with self-assessed estimates of probabilities in this measure. The COVID-19 Preventive Behavior Index (CPBI) reflects people's own estimates of their likelihood to behave in particular ways. It is an index of the subjective likelihood that someone will engage in COVID-19 preventive behaviors. The clarity and specificity of its purpose makes the CPBI amenable to being used in conjunction with other scales that are helpful in monitoring and predicting behavior change during the pandemic.

Methods

Ethics

The study received ethics approval from Nottingham Trent University's College of Business, Law and Social Sciences

Research Ethics Committee (ref: 2020/191). All participants provided informed consent online.

Participants

We recruited 479 individuals, of whom 470 answered all questions. Only data from these 470 individuals were analyzed. Three hundred and three (64.47%) were female, 165 (35.11%) were male, and two were gender non-binary (0.43%). The age range was 18–72 years ($M = 32.67$, $SD = 12.35$). The sample included an even distribution of White British and Black, Asian, and Minority Ethnic (BAME) individuals. Details on the social and demographic characteristics are reported in Table 1.

Design and Procedure

Data were collected at two points during the COVID-19 outbreak in the United Kingdom: 8 July ($N = 251$) and 14 August 2020 ($N = 228$). All participants were recruited on *Prolific*, an online platform for participant recruitment. They were invited to participate in a cross-sectional survey study of preventive behavior in response to the pandemic. Finally, all participants received appropriate debriefing, including information on support and counseling, and were compensated for their time.

Measures

Perceived risk of COVID-19. The COVID-19 Own Risk Appraisal Scale (CORAS) (Jaspal et al., 2020) was used to assess perceived own risk of COVID-19. It includes six items scored on a 5-point ordinal scale assessing the perceived risk of COVID-19. A higher total score represents a higher perceived personal risk of COVID-19 ($\alpha = 0.87$).

Fear of COVID-19. The Fear of COVID-19 Scale (Ahorsu et al., 2020) includes nine items measuring the fear of COVID-19. It is scored on a 5-point scale (1 = strongly disagree, 5 = strongly agree). A higher total score corresponds to greater fear of COVID-19 ($\alpha = 0.82$).

COVID-19 preventive behaviors index (CPBI). The CPBI measures the perceived likelihood of engaging in behaviors aimed at reducing exposure to SARS-CoV-2 and COVID-19. Items reflect international commonalities in governmental guidance for their populations current in the first 6 months of the pandemic (e.g. US & UK Centers for Disease Control and Protection statements). Items used in other studies of COVID-19 prevention behaviors were also examined to ensure overlap where possible in specific items (in order to allow subsequent comparisons across studies). The CPBI was constructed to provide a short, reliable and valid measure reflecting the major types of preventive behaviors open to individuals. Items 8 and 9 were reverse scored. The final 10 items (listed in Online Appendix 1), each scored on a 5-point scale (1 = strongly disagree, 5 = strongly agree), were then administered to two

Table 1. Social and Demographic Characteristics of Participants.

| Variables | Total (N = 470) | Females (N = 303) | Males (N = 165) | Non-Binary (N = 2) | p ^a |
|-----------------------------|-----------------|-------------------|-----------------|--------------------|----------------|
| Age (years) | | | | | |
| M (SD) | 32.7 (12.4) | 32.6 (12.0) | 32.9 (13.0) | 21.0 (4.2) | 0.399 |
| Ethnicity (detailed) | | | | | 0.179 |
| N (%) | | | | | |
| White British | 243 (52) | 169 (56) | 74 (45) | 0 (0) | |
| White and Black Caribbean | 4 (1) | 3 (1) | 1 (1) | 0 (0) | |
| White and Asian | 5 (1) | 3 (1) | 2 (1) | 0 (0) | |
| White Other | 2 (0) | 0 (0) | 2 (1) | 0 (0) | |
| Pakistani | 57 (12) | 34 (11) | 22 (13) | 1 (50) | |
| Bangladeshi | 15 (3) | 7 (2) | 8 (5) | 0 (0) | |
| Indian | 68 (15) | 40 (13) | 28 (17) | 0 (0) | |
| Caribbean | 28 (6) | 18 (6) | 9 (5) | 1 (50) | |
| African | 48 (10) | 29 (10) | 19 (12) | 0 (0) | |
| Ethnicity (main) | | | | | 0.027 |
| N (%) | | | | | |
| White British | 243 (52) | 169 (56) | 74 (45) | 0 (0) | |
| BAME | 227 (48) | 134 (44) | 91 (55) | 2 (100) | |
| Qualification | | | | | 0.232 |
| N (%) | | | | | |
| High School (GCSE/O-Levels) | 48 (10) | 21 (7) | 26 (16) | 1 (50) | |
| High School (AS/A-Levels) | 139 (30) | 93 (31) | 46 (28) | 0 (0) | |
| Undergraduate | 197 (42) | 134 (44) | 62 (38) | 1 (50) | |
| Postgraduate | 73 (16) | 45 (15) | 28 (17) | 0 (0) | |
| Apprenticeship | 5 (1) | 4 (1) | 1 (0) | 0 (0) | |
| Other | 7 (1) | 5 (2) | 2 (1) | 0 (0) | |
| None | 1 (0) | 1 (0) | 0 (0) | 0 (0) | |
| Employment | | | | | 0.708 |
| N (%) | | | | | |
| Employed | 239 (51) | 157 (52) | 82 (50) | 0 (0) | |
| Self-employed | 37 (8) | 22 (7) | 15 (9) | 0 (0) | |
| Furloughed | 31 (7) | 19 (6) | 12 (7) | 0 (0) | |
| Student | 114 (24) | 72 (24) | 40 (24) | 2 (100) | |
| Retired | 10 (2) | 7 (2) | 3 (2) | 0 (0) | |
| Unemployed | 39 (8) | 26 (9) | 13 (8) | 0 (0) | |

^aResults from parametric bivariate tests of significance (t-test or ANOVA where appropriate for continuous variables and χ^2 test of independence for categorical variables).

samples of participants, as described in this article. A higher score indicated a greater likelihood of engaging in preventive behaviors ($\alpha = 0.75$).

Statistical Analyses

We used Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Item Response Theory (IRT) with differential item functioning (DIF).

Four criteria informed the assessment of the dimensionality of the CPBI: (i) Parallel analysis (Horn, 1965), (ii) the very simple structure method (Revelle & Rocklin, 1979), (iii) Velicer's (1976) minimum average partial test, and (iv) the analysis of the internal consistency and interpretability of the factor solution.

The theoretical solution obtained through EFA was tested by means of CFA. We tested the measurement model identified through EFA by using structural equations and evaluating the goodness of the model's fit to the empirical correlation matrix. We assumed our data to be ordinal, so we used polychoric

correlations to fit both EFA (weighted least square; Schmitt, 2011) and CFA models (weighted least square mean and variance, with robust standard errors; Muthén, 1983). We analyzed the reliability of the solution by means of McDonald's (1999) Omega (Green & Yang's formula 21, 2009).

Last, we used IRT to investigate item properties, performance, and differential functioning. In particular, we utilized the graded response function to fit the model (Samejima, 1969) and plotted results by means of item response categories characteristic curves, item information curves, and test information curves.

Prior to fitting the model, we tested for the assumption of local independence. In fact, IRT relies on two fundamental assumptions, namely unidimensionality and local independence, with the latter representing the degree of conditional independence of items given the scoring on the latent dimension (Linacre, 2009). We estimated item residual correlations and considered correlations greater than the absolute average residual correlation +0.20 as indicating local dependence.

Table 2. CPBI Correlation Table.

| | M | SD | Skewness | Kurtosis | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---------|------|------|----------|----------|---------|---------|---------|---------|---------|---------|---------|---------|-------|----|
| Item 1 | 3.99 | 1.14 | −1.06 | 0.13 | | | | | | | | | | |
| Item 2 | 3.89 | 1.21 | −0.99 | −0.08 | 0.34*** | | | | | | | | | |
| Item 3 | 3.89 | 1.34 | −1.03 | −0.15 | 0.30*** | 0.22*** | | | | | | | | |
| Item 4 | 3.9 | 1.2 | −0.91 | −0.25 | 0.45*** | 0.37*** | 0.36*** | | | | | | | |
| Item 5 | 4.55 | 0.94 | −2.25 | 4.43 | 0.26*** | 0.26*** | 0.19*** | 0.45*** | | | | | | |
| Item 6 | 4.66 | 0.65 | −2.42 | 7.47 | 0.33*** | 0.27*** | 0.17*** | 0.29*** | 0.40*** | | | | | |
| Item 7 | 3.98 | 1.04 | −1.01 | 0.36 | 0.26*** | 0.20*** | 0.14** | 0.26*** | 0.23*** | 0.26*** | | | | |
| Item 8 | 3.94 | 1.12 | −0.99 | 0.2 | 0.20*** | 0.25*** | 0.21*** | 0.31*** | 0.31*** | 0.23*** | 0.25*** | | | |
| Item 9 | 2.87 | 1.2 | 0.32 | −0.99 | 0.38*** | 0.18*** | 0.20*** | 0.37*** | 0.19*** | 0.13** | 0.17*** | 0.15*** | | |
| Item 10 | 4.21 | 1.09 | −1.49 | 1.49 | 0.27*** | 0.29*** | 0.17*** | 0.26*** | 0.28*** | 0.29*** | 0.31*** | 0.26*** | 0.10* | |

Note. M and SD represent mean and standard deviation, respectively. All correlations are expressed as Spearman's ρ values.

*** indicates $p < 0.001$. ** indicates $p < 0.01$. * indicates $p < 0.1$.

We investigated item differential functioning by means of the logistic regression/IRT method (Choi et al., 2011). In particular, we analyzed differential functioning by gender (females, males) and age (<30 years, ≥ 30 years), and for this purpose we had to recode the relevant variables into categorical variables, when required. We used an overall χ^2 likelihood ratio test ($\alpha = 0.01$) as the detection criterion and McFadden's pseudo R^2 change (significant change = 0.02) to measure the magnitude of differential item functioning (Choi et al., 2011; Swaminathan & Rogers, 1990). Finally, the concurrent validity of the CPBI was tested by correlating CPBI scores with CORAS and total Perceived Fear of COVID-19 scores, respectively. We used the Spearman's ρ correlation coefficient.

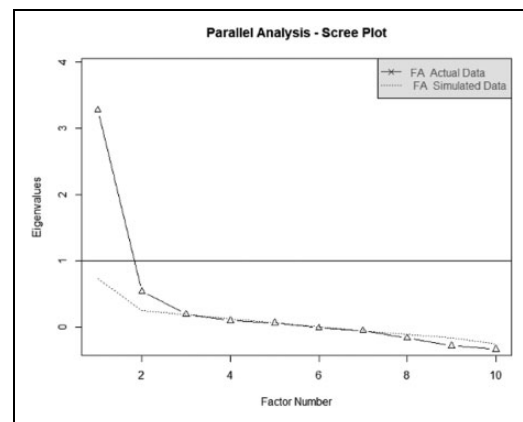
Prior to running the analyses, we split the total sample ($N = 470$) into two sub-samples of equal size, selected at random, each displaying similar properties with regard to the participants' socio-demographic characteristics. EFA was conducted with the first sub-sample ($N = 235$), whereas CFA and IRT were conducted with the second sub-sample ($N = 235$). However, preliminary data screening and the study of validity were conducted on the total sample ($N = 470$).

We used the statistical programming language R (Version 3.6.2) (R Core Team, 2016) to perform all analyses, in particular: psych (Revelle, 2020) for EFA, lavaan (Rosseel, 2012) for CFA, semTools (Jorgensen et al., 2020) for reliability, and mirt (Chalmers, 2012) for IRT, lordif for DIF (Choi et al., 2011), and furniture for tables (Barrett & Brignone, 2017).

Results

Preliminary Data Screening

We found no patterns of unengaged responses ($SD < 0.3$). All the CPBI items showed values skewness and kurtosis within the range of ± 1.50 , except for two cases (Item 5 = -2.25 , 4.43; Item 6 = -2.42 , 7.47). The CPBI items intercorrelated positively and significantly ($p < 0.1$), ranging from 0.10 to 0.45. Table 2 shows detailed items' descriptive statistics and correlations.

**Figure 1.** Exploratory factor analysis, scree plot.

Exploratory Factor Analysis

We ran EFA on the polychoric correlation matrix of the CPBI ($N = 235$) (TLI = 0.75, RMSEA = 0.12 with 90% CI = 0.11–0.14, BIC = -29.61). Results from parallel analysis indicated that three factors were best candidates to summarize the structure of the CPBI. Specifically, the three factors had eigenvalues greater than the randomly extracted eigenvalues, although only the first factor had an empirical eigenvalue greater than one (First Factor = 3.28; Second Factor = 0.53) (Figure 1). When we examined the pattern matrix of the three-factor solution, we found that it was poorly interpretable, with inadequate internal consistency of factors, less than three items loading onto one of the three factors, and item-cross-loading onto two or more factors.

For this reason, we decided to inspect the dimensionality of the scale in depth. The very simple structure method goodness-of-fit index achieved a maximum of 0.73 in correspondence of one factor and, similarly, the minimum average partial test indicated a minimum of 0.03 with one factor. We then inspected the pattern matrix extracted from the one-factor solution, and we found that all items loaded adequately (≥ 0.41) onto a single factor, achieving a satisfactory internal consistency ($\alpha = 0.75$, with 95% CI = 0.69–0.79), with no item

Table 3. CPBI Exploratory Factor Analysis.

| Item Number | One-Factor Solution | | | Three-Factor Solution | | | | |
|--|---------------------|---------------------|------------------|-----------------------|-------|-------|---------------------|------------------|
| | FI | Item Communality | Item Variance | FI | F2 | F3 | Item Communality | Item Variance |
| <i>How likely is that, during the COVID-19 outbreak, that you will . . .</i> | | | | | | | | |
| 1. Keep a distance of 2 meters in your everyday interactions with people outside of your household | 0.58 | 0.33 | 0.67 | 0.19 | 0.36 | 0.25 | 0.40 | 0.60 |
| 2. Use a facemask when you leave your home | 0.52 | 0.27 | 0.73 | 0.19 | 0.07 | 0.38 | 0.29 | 0.71 |
| 3. Work from home, if possible | 0.41 | 0.16 | 0.84 | −0.18 | 0.06 | 0.68 | 0.39 | 0.61 |
| 4. Avoid any non-essential local travel | 0.80 | 0.64 | 0.36 | 0.28 | 0.06 | 0.66 | 0.75 | 0.25 |
| 5. Avoid any non-essential international travel | 0.77 | 0.59 | 0.41 | 0.86 | −0.06 | 0.07 | 0.79 | 0.21 |
| 6. Wash your hands regularly | 0.61 | 0.37 | 0.63 | 0.68 | 0.12 | −0.08 | 0.46 | 0.54 |
| 7. Keep informed about COVID-19 in the UK by watching the news | 0.48 | 0.23 | 0.77 | 0.52 | 0.16 | −0.09 | 0.29 | 0.71 |
| 8. Not make any changes to your lifestyle | 0.51 | 0.26 | 0.74 | 0.34 | 0.02 | 0.23 | 0.26 | 0.74 |
| 9. Continue to see people outside of your household | 0.41 | 0.17 | 0.83 | −0.02 | 0.85 | 0.02 | 0.72 | 0.28 |
| 10. Comply with the NHS track and trace service, if contacted | 0.50 | 0.25 | 0.75 | 0.46 | −0.07 | 0.16 | 0.29 | 0.71 |
| Total variance explained | 33% | | | 22% | 14% | 10% | | |
| Cronbach's α | 0.75 | | | 0.66 | 0.53 | 0.57 | | |

increasing α if deleted. The one-factor solution was theoretically sound and interpretable and, therefore, we retained it for further analyses. We report a comparison of the one-factor and the three-factor solution in Table 3.

Confirmatory Factor Analysis

We ran CFA on the second random sub-sample ($N = 235$), testing the one-factor model previously identified through EFA. The model showed acceptable fit ($CFI = 0.94$, $TLI = 0.92$, $RMSEA = 0.61$, $SRMR = 0.07$) and reliability (McDonald's $\Omega = 0.80$).

Item Response Theory

We fit the graded response model with free estimation of item parameters, and we compared its fit to the fit of a model in which item parameters were constrained to be equal (Rizopoulos, 2006). The model accounting for free estimation showed the best fit ($AIC = 5,531.61$, $BIC = 5,673.45$, $\log Lik = -2,724.80$, marginal reliability = 0.80), with $p < 0.001$, compared to the constrained model ($AIC = 5,518.39$, $BIC = 5,691.37$, $\log Lik = -2,709.19$, marginal reliability = 0.78). Based on these results, we moved on estimating the residual correlation matrix from the unconstrained model. The absolute average residual correlation was 0.02, with a critical value of 0.22 for local dependence. We observed 11 item pairs showing positive correlations and 34 showing negative correlations. Among the latter, six pairs had values significantly greater than the critical value, in absolute terms, indicating local dependence.

Regarding item parameters, we found that Item 4 ($\alpha = 1.94$), Item 5 ($\alpha = 1.81$), and Item 1 ($\alpha = 1.74$) were the most discriminating items, whilst Item 3 ($\alpha = 0.99$), Item 7 ($\alpha = 0.96$), and Item 8 ($\alpha = 0.90$) were the least discriminating. Moreover, items 3, 5, 6, 7, 8, 9, 10 presented violation of the assumptions of the graded response model. In fact, their thresholds tended to disperse in a disordered fashion, particularly for category 3 and category 4, thus indicating that collapsing the two categories may improve item calibration and targeting of respondents. Table 4 presents item parameters, whereas Figure 2 (in Online Appendix 2) presents item response categories characteristic curves.

Regarding item information, Item 4 (16.97%), Item 1 (15.38%), and Item 6 (13.25%) provided the greatest contribution in terms of information, vs. Item 7 (6.58%), Item 3 (5.75%), and Item 8 (5.66%), the least informative items. Figure 3 and Figure 4 (in Online Appendices 3 and 4) show item information curves and the test information curve, respectively.

To test for differential item functioning by gender and age, we recoded gender and age. Because too few non-binary gendered individuals ($N = 2$) participated in the study, their responses were dropped, whereas regarding age, we classified responses into two ordinal groups: (1) responses by participants aged < 30 years vs. responses by participants aged ≥ 30 years, respectively. We found differential item functioning by gender for Item 6 ($p < 0.001$, $R^2 = 0.03$) and Item 7 ($p < 0.01$, $R^2 = 0.02$). Regarding Item 6, slope parameter estimates were higher in men ($\alpha = 1.89$) than in women ($\alpha = 1.69$). However, the item true score function showed that women scored higher than men across the theta continuum. The absolute difference

Table 4. CPBI Graded Response Model, Standardized Item Parameters' Estimates and errors (N = 235).

| Item Number | α | SE | $\beta 1$ | SE | $\beta 2$ | SE | $\beta 3$ | SE | $\beta 4$ | SE |
|-------------|----------|------|-----------|------|-----------|------|-----------|------|-----------|------|
| Item 1 | 1.74 | 0.26 | 4.74 | 0.51 | 2.47 | 0.29 | 1.74 | 0.25 | -0.49 | 0.20 |
| Item 2 | 1.28 | 0.20 | 3.50 | 0.35 | 2.00 | 0.23 | 1.37 | 0.20 | -0.41 | 0.17 |
| Item 3 | 0.99 | 0.18 | 2.29 | 0.23 | 1.87 | 0.21 | 1.12 | 0.18 | -0.09 | 0.16 |
| Item 4 | 1.94 | 0.29 | 4.24 | 0.46 | 2.36 | 0.30 | 1.49 | 0.25 | -0.50 | 0.21 |
| Item 5 | 1.81 | 0.33 | 4.49 | 0.53 | 3.67 | 0.44 | 2.64 | 0.35 | 1.80 | 0.29 |
| Item 6 | 1.73 | 0.32 | 6.07 | 0.85 | 5.25 | 0.65 | 3.76 | 0.43 | 1.50 | 0.26 |
| Item 7 | 0.96 | 0.17 | 3.65 | 0.37 | 2.25 | 0.23 | 1.28 | 0.18 | -0.80 | 0.16 |
| Item 8 | 0.90 | 0.17 | 3.29 | 0.32 | 2.16 | 0.22 | 1.15 | 0.17 | -0.46 | 0.16 |
| Item 9 | 1.02 | 0.18 | 2.44 | 0.24 | 0.08 | 0.16 | -0.83 | 0.17 | -2.01 | 0.22 |
| Item 10 | 1.11 | 0.20 | 3.77 | 0.38 | 2.70 | 0.27 | 1.89 | 0.22 | 0.30 | 0.17 |

between the item true-score function peaked at about $\theta = -1$, although such difference was in a region of θ that was not the most represented in the population. Regarding Item 7, women ($\alpha = 1.12$) showed higher slope parameters than men ($\alpha = 0.94$), but men scored higher than women at this item across the θ continuum, with the difference peaking at about $\theta = -2$, also in this case a region of θ holding very low impact. We did not find differential item functioning by age.

Convergent and Criterion Validity

The CPBI correlated significantly ($p < 0.001$) with the CORAS (Spearman's $\rho = 0.21$, $N = 470$) and with the Fear of COVID-19 Scale (0.27), respectively, indicating the concurrent validity of the scale.

Discussion

The analysis of the statistical properties of the CPBI indicated that it is reasonable to treat the 10 items as a unidimensional measure of self-reported likelihood of engaging in preventive activity. Analysis of the correlations of the CPBI with scales measuring fear of COVID-19 and perceived personal risk of COVID-19 indicate its concurrent validity. Perceived likelihood of preventive behavior is positively correlated with fear and risk, which conforms with the suggestion that greater fear and perceived risk of COVID-19 may be prompting people to engage in preventive activity (Harper et al., 2020; Lee & You, 2020). The average likelihood of adopting prevention measures was moderately high. Like other studies (e.g. Daoust, 2020), we found no substantive effects for age and gender in most preventive behaviors. However, we found that women generally reported higher likelihood of washing their hands and that men reported higher likelihood of keeping themselves informed about COVID-19.

The CPBI measures how likely the individual is to adhere to prevention guidance across a range of behaviors. These behaviors encompass social distancing, self-isolation, hygiene, and virus testing and tracking, plus staying informed. The CPBI items are couched in such a way as to encompass the relatively small variations in prevention guidelines that have been

occurring across time and location. This makes the CPBI a potentially useful tool for monitoring change over time and for comparisons across research studies. The two items currently mentioning the UK and National Health Service (NHS) can be adjusted to enable the CPBI to be used internationally and across healthcare systems.

The CPBI can and should be elaborated as new preventive measures are introduced. The question of vaccination uptake was not included in this version of the scale because a medically acceptable vaccine was not available at the time of this study. No vaccine was expected to be generally available for at least 9 months. Asking people about their likelihood of having a hypothetical vaccine, while interesting, is substantively different from asking them about behaviors they can do currently. Once vaccines are available, questions concerning vaccination for COVID-19 will need to be included in the CPBI. Exploring the issue of COVID-19 vaccination hesitancy is important, especially in light of various conspiracy theories advocating vaccination rejection (Earnshaw et al., 2020).

While individual items in the CPBI can be used to examine predictions about particular behaviors, its prime purpose is to provide an overall estimate of the individual's likelihood of participating in personal efforts to protect against COVID-19. As such, it is clearly not a measure of actual behavior. It is also not technically a measure of intention to act. The items do not ask about what people intend to do; they address the likelihood of doing something. As such, the CPBI explores the territory between intention and action. As Gollwitzer (1999) pointed out, there is typically an intention-behavior gap because intention can be a weak determiner of action. In fact, Gibson et al. (2020) claimed that capability, opportunity and motivation mediated between intention and behavior with regard to enacting hygiene guidance during the early stages of the COVID-19 outbreak in the UK.

Indeed, there may be coercive, pervasively shared social representations that any given behavior is desirable or even necessary during the pandemic (Hagger et al., 2020), which prompt individuals to say that they intend to adopt that behavior in the future (Jaspal & Nerlich, 2020). Yet, intentions aside, people are generally able to recognize the likelihood that they will actually adopt that behavior when other intervening factors are taken into account, such as their ability to adopt the

behavior, the potential impact of behavior change on their sense of self-esteem, how the behavior will be regarded by others in their social context and so on. This line of thinking is consistent with Identity Process Theory (Breakwell, 2015; Breakwell & Millward, 1997), which recognizes that the relationship between social representation and action is mediated by social and psychological factors, such as identity concerns. It is for this reason that a measure of likelihood is necessary. The CPBI taps into the individual's own estimate of the likelihood that the behavior will actually occur. This estimate can factor in the self-perception of capability, opportunity and motivation. It may also allow for face-saving strategies the individual recognizes will affect behavior (Daoust, 2020). Consequently, the CPBI may be a more useful index for policy makers and health professionals than a straightforward measure of intention since it may be a better prediction of actual behavior.

Conclusion

The CPBI is an internally reliable measure of self-reported likelihood of engaging in COVID-19 preventive behavior that has good concurrent validity. A useful next step will be to examine the relationship between self-reported likelihood and both behavioral intentions and actual behavior. The CPBI is adaptable enough to be used over time as a monitoring instrument by policy makers and a modeling tool by researchers. Findings from studies using the CPBI will be useful to policy makers because knowing what people say they are likely to do can be the platform for further intervention, particularly for refining the nature of prevention guidance because it identifies what people are not expecting to do.

Data Availability Statement

Ethical approval was given on the understanding that participants' data would not be made publicly available. However, individual researchers may contact the corresponding author for access to the data.


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Supplemental Material

Supplemental Material for this article is available online.

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