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Original Research

Pros and cons factors influence population attitudes toward non-pharmaceutical interventions and vaccination during post-COVID-19

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ABSTRACT

Objectives: Population compliance greatly influences the effectiveness of vaccination and non-pharmaceutical interventions (NPIs) for the curtailting of COVID-19 transmission. We aimed to determine the conceptual framework of potential factors that influence compliance.

Study design: This was a cross-sectional study.

Methods: Questionnaires were used to survey population attitudes toward vaccination and NPIs in China. Confirmatory factor analysis of the survey data by structural equation model was used to define the pros and cons factors of attitudes. The strength and direction of each factor’s effect on population attitudes were illustrated by Bayesian network analysis.

Results: A total of 1700 respondents aged 18–70 years were surveyed with a panel of 34 questionnaires. Of these questionnaires, the confirmatory factor and structural equation model analysis identified five categories contributing to positive attitudes, including response efficiency, willingness and behavior, trust, cues to action, and knowledge, as well as four categories contributing to negative attitudes, including autonomy, perceived barriers, threat, and mental status. Bayesian networks revealed that cues to action produced a driving force for positive attitudes, followed by willingness and behavior, trust, response efficiency, and knowledge, whereas perceived barriers produced a driving force for negative attitudes, followed by autonomy and threat.

Conclusions: This study established a concise and representative list of questionnaires that could be applied to investigate the conceptual framework of potential pros and cons factors of attitudes toward vaccination and NPIs for COVID-19 prevention. The factors with driving forces should be addressed with a priority to effectively improve population compliance.

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Introduction

As of November 2021, the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has been raging globally. Many countries are experiencing multiple waves of high COVID-19 transmission. Infectious diseases and human behaviors are generally intertwined. People’s movements and interactions are the engines of transmission. The COVID-19 pandemic has significantly changed our daily activities, which in turn greatly influence the development of the pandemic. So far, although vaccination has been administered in many parts of the world, no satisfactory drugs have been developed to curtail the rapid transmission of COVID-19. Most countries have implemented administrative measures to timely contain the spread of COVID-19. These measures are usually referred to as non-pharmaceutical interventions (NPIs), such as quarantine and lockdowns, social distancing measures, community use of facemasks, and travel restrictions. Vaccines are also given to curb the transmission of COVID-19. However, these measures have resulted in the significant impairment of physical and psychosocial well-being of people. Such impairment often existing vaccine hesitancy among subgroups of people led to declined compliance to abide requirements, which drastically affected the effectiveness of control of COVID-19 transmission.

Earlier studies have identified a few underlying factors that might influence population compliance with NPIs and vaccination.
through questionnaire surveys designed on the basis of several psychological theories, such as health belief model, perceived stress, protection motivation theory, theory of planned behavior, as well as sociodemographic factors. These previous studies were independently implemented, often focusing on individual aspects of potential factors, although the actual factors were usually interrelated to affect people’s decisions. In the realistic world, several manifesting variables can form a latent variable that, despite the difficulty to be measured, is often more representative of people’s overall attitude and social status. As to the psychological survey for attitudes toward COVID-19 prevention, a latent variable approach that integrates several aspects of influencing factors to obtain a comprehensive conclusion is more applicable in judging population attitudes. Routine statistical methodology is often incapable to dig out the representative latent variables and their complex interrelationships.

Investigating factors affecting population compliance with vaccination and NPIs by survey often yields a multitude of categorical data, which needs more specialized mathematical tools to analyze. Structural equation model (SEM) combines latent variable approach, path analysis, and framework analysis, achieving simultaneous analysis of complex relationships of categorical factors. Another mathematical technology is Bayesian paradigm that can provide information about effect direction and causal inference of a series of factors that influence people’s attitudes.

People were reported to display varied overall attitudes toward vaccination and NPIs for the prevention of COVID pandemic; we hypothesized there were distinctive factors resulting in positive and negative responses. We aimed to apply SEM and Bayesian methods to analyze the conceptual framework and driving force of factors that affected population attitudes. This study would develop a concise and representative list of questionnaire items, which could be applied to investigate the comprehensive factors resulting in positive and negative responses toward NPI and vaccination for COVID-19 prevention.

Methods

Study design and setting

We conducted a face-to-face questionnaire survey about population attitudes toward NPIs and vaccination of COVID-19 from August 1 to August 20, 2021, in Ningbo city, China. The participants were aged 18–70 years. The sample size was calculated based on the online Raosoft sample size calculator (http://www.raosoft.com/samplesize.html), which used a response rate of 80%, a confidence interval of 99%, a largest population of 20,000, and a margin of error of 5%; the required sample size was 416. Accordingly, this study included 1700 subjects that were enough for the present study. We recruited participants via convenience sampling at three communities, a college, a park, and an outpatient department. The participants were interviewed by a trained surveyor. The process comprised five phases: involving questionnaire item definition and validity, reliability validity, structure validity of confirmatory factor analysis, strength and direction of factorial effect, and finally, interpretation by experts. The survey raters were trained with knowledge about the meaning of questions and the way of communication with participants.

Questionnaire items and surveys

The questionnaire items consisted of contents based on three theories: perception of severity and susceptibility of COVID-19, perception of benefit and barriers of NPI and vaccine, and knowledge about COVID-19 based on the health belief model, threat assessment of COVID-19 and response efficiency based on the protection motivation theory, as well as cues to action, and willingness and behavior based on the theory of planned behavior. The questionnaire items also included assessment of mental anxiety and depression; trust of medicine, government, and vaccine; as well as autonomy of respondents. These items were reviewed by a panel of experts, including two psychologists, a statistician, and an epidemiologist. Except that 2-item Patient Health Questionnaire (PHQ-2) and 2-item Generalized Anxiety Disorder (GAD-2) were 4-point (0–3) scales, each item developed in the present study was 5-point (0–4) Likert scale with answers of strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. The consistency between the statement in the questionnaire and the theoretical indicative meaning was assessed by experts. The questionnaires were amended according to the comments of the experts and pilot tested by a small group of candidates ahead of the large-scale formal investigation. The demographic information of the participants consisted of age, sex, occupation, education, marriage, and residence. The questions and their abbreviations were supplied in Supplement 1.

Analysis

Reliability of the data was considered acceptable when Cronbach’s alpha exceeded 0.8. The sampling adequacy for factor analyses was verified using Kaiser–Meyer–Olkin test (at least >0.7). Each category of factors was denoted as a latent variable that was represented by three to four questionnaire items. The confirmatory factor analysis was applied to verify and illustrate the conceptual framework using SEM in the lavaan R package. The final component items of a latent variable were determined according to five metrics of SEM, including Chi-squared (<0.05), standardized root mean square residual (<0.1), comparative fit index (>0.9), root mean square error of approximation (<0.1), and loadings (>0.6). We used the psych R package to compute the polychoric correlation network and the qgraph R package to demonstrate the network. The qgraph package produced regularized partial correlations using the lasso method by the glasso R package. Edges of the network ranging from 0.4 to 0.9 were accepted as reliable associations. The thickness of edges indicated the magnitude of association between two nodes.

To create a Bayesian network of directed acyclic graphs (DAGs), we applied the Bayesian hierarchical model using the bnlearn R package. The fit process of Bayesian network involved the specification of edges, strength of connections, and probability of direction. The edges were determined using a hill climbing algorithm to learn the structure of network and its parameters. The bootstrap function computed the structure of network represented by edges according to goodness-of-fit target score (e.g. Bayesian information criterion [BIC]). The BIC was used as a criterion for edge strength. The smaller the BIC value, the stronger the connection. The direction of connection between nodes was represented by a probability. Each edge had a strength value and a direction value, both of which were expressed in a rate of 0–1. We kept the edges with strength >0.8. The thickness of an edge reflected the magnitude of its strength value. The software codes were supplied in Supplement 2.

Statistical analysis

The answers were represented by numbers of 0 through 3 or 4. Their prevalence was calculated. Categorical variables of demographic information were expressed as absolute values and percentages, and the differences in their distribution were tested by the Chi-squared test when necessary. Age was classified into three groups of 18–29, 30–50, and >50 years. Income was classified into...
three categories of <4000, 4000–8000, and ≥8000 Chinese Yuan. Residence was denoted as urban and rural. Job status was classified as medical staff, other employed, retired, student, and unemployed. Education levels were denoted as below college and at least college.

Results

Questions and latent variables

Descriptive demographic characteristics of the respondents are provided in Table 1 and Fig. 1. Of 1700 respondents who were aged 18–70 years, 49.5% were female (n = 842), and 61.5% (n = 1046) were married. 75% (n = 1276) held a college or higher academic degree. The job status comprised medical staff (n = 233 [13.7%]), other employed (n = 1070 [62.9%]), retired (n = 53 [3.1%]), student (n = 187 [11%]), and unemployed (n = 157 [9.2%]). The distribution of monthly income was under 4000 (n = 338, 19.9%), 4000–8000 (n = 685, 40.3%), and ≥8000 (n = 677, 39.8%) Chinese Yuan. Overall, 81.2% (n = 1380) lived in urban areas, and 18.8% (n = 320) in rural areas. Fig. 1 illustrates the composition percentages of answers to 34 questions among 1700 respondents in terms of Likert scale, showing the distribution of answers for each question was distinctive. We classified the people into three age groups of 18–29, 30–50, and >50 years and compared the Likert scores among the age groups. Generally, the comparison showed that young people had a higher prevalence of depression and anxiety and a higher level of knowledge, whereas the older people had a higher level of autonomy (Table 2). Other categories of questions were the same or only one question showed different responses.

Before exploratory factorial analysis, we inspected the correlation matrix of the questionnaire items. Bartlett’s Chi-squared was 4751.2 (P < 0.001), indicating that the correlation matrix was not an identity matrix. The mean value of Kaiser–Meyer–Olkin test was 0.86 (ranging from 0.71 to 0.96) that was more than 0.7 as required for adequate sampling for factor analysis. Cronbach’s alpha was 0.94, indicating reliability of the survey data. Finally, 34 questions among 1700 respondents in terms of Likert scale, were referred to as the following latent variables: mental depression and anxiety, willingness and behavior, knowledge, perceived barriers, response efficiency, cues to action, autonomy, trust, and threat (Supplement 1 and Fig. 2). To fit variable labels inside the nodes of network, we used the abbreviations for the questions.

Confirmatory factor analysis

Confirmatory factor analysis by SEM showed that nine latent variables composed of 34 items were classified into two classes (Fig. 2). One class contained five latent variables contributing to positive responses, the loadings of which were greater than zero: response efficiency (loading = 1), willingness and behavior (loading = 0.97), trust (loading = 0.85), cues to action (loading = 0.76), and knowledge (loading = 0.59). Another class contained the remaining four latent variables contributing to negative responses: autonomy (loading = 0.94), perceived barriers (loading = 0.9), threat (loading = 0.3), and mental (loading = 0.28). The present results proved that willingness and behavior, response efficiency, and trust had a larger positive effect than cues to action and knowledge, whereas perceived barriers and autonomy had a massively negative effect.

Network

The polychoric correlation network depicted the associations between nine latent variables or categories of 34 questions (Fig. 3). The edges with correlation coefficient between 0.4 and 0.9 were kept. The thickness of the edges reflected the centrality degree (strength). Based on the magnitude and strength of correlation, we identified that willingness and behavior, trust, cues to action, and response efficiency had the core influence and prominent interrelationship in the correlation network, whereas autonomy and perceived barriers had negative correlation with the network core. The mental status, knowledge, and threat seemed to be isolated from the central correlation network.

As to the Bayesian network in the appearance of DAG, its primary difference from the polychoric correlation network was that the Bayesian network had a feature of direction. This feature represented a causal relationship or effect direction in the network (Fig. 4). The present DAG showed that the mental status (Nodes 1–4 in Fig. 4) was an isolated factor without an evident effect on other latent variables. Three nodes (Nodes 22, 23, and 21) belonging to cues to action were on the top of the DAG, implying that these factors were the original driving force of the DAG. The subsequent effect chains stretched in an order of willingness and behavior (Nodes 6, 5, 7, and 8), trust (Nodes 30, 28, and 29), response efficiency (Nodes 18, 17, 19, and 20), and, finally, knowledge (Nodes 9–12). On the right segment of the DAG, three items belonging to perceived barriers had the original negative effect of the DAG, followed by autonomy and threat. To be noteworthy, one item of perceived barriers, that is, difficult to get self-protection, was at the end of the DAG. The strength and direction values of links between every two nodes were provided in Supplement 3.

Discussion

The present study coined a panel of 34 questionnaire items and determined their conceptual framework and interrelationship that might affect the population attitudes toward NPI measures and vaccination for prevention of the COVID-19 pandemic. SEM and confirmatory factorial analysis of the survey results of 1700 respondents showed that five categories of questionnaire items producing positive effects and four categories producing negative
effects on the overall population attitudes. The Bayesian network approach proved that cues to action produced a positive driving force of the network, whereas perceived barriers produced a negative driving force of the network.

So far, a number of preceding studies investigated potential factors that affected people’s attitude toward NPIs and vaccination.29,30 These factors were related to multidisciplinary fields that could be largely generalized into three theories: including health belief model, protection motivation theory, and the theory of planned behavior. However, these studies failed to clarify the conceptual framework of numerous factors, their interrelationship, and effect direction. The present study applied three approaches to disentangle the complex factorial network: involving the definition of latent variables, confirmatory factor analysis by SEM, and Bayesian network approach.

We classified these factors into nine categories of concepts based on the three theories and previous literature. Although age is an important factor that influences people’s attitude in many ways, our results by age stratification showed difference only in depression and anxiety, knowledge, and autonomy (Table 2). Other categories of questions were the same or only one question showed different responses (Table 2). These categories were depicted by SEM and referred to as latent variables. Latent variables are inferred variables representing a centralized value shared by the observed variables or the degree to which observed variables congregate in meaning.31 Observed variables, which appear as components of a latent variable, must correlate with each other to some extent. Too low the correlation coefficient between observed variables means they do not belong to the same latent variable, whereas too high the correlation coefficient means they are redundant.32 We specified a correlation coefficient of 0.4—0.9 as the threshold value for the observed variables in a latent variable (Fig. 3). This correlation network showed how close the categories were interlinked. The network showed that response efficiency, willingness and behavior, cues to action, and trust formed the center of the positive response segment, whereas autonomy and perceived barriers formed the negative response segment.

The SEM analysis of latent variables successfully fitted the survey data to yield a conceptual framework consisting of positive and negative categories of items (Fig. 2). This fitted structure of latent variables vividly depicted the relative effectiveness of potential factors leading to positive and negative responses toward NPI and vaccination and answered our hypothesis. In the SEM path diagram, the loading values on the edges illustrated the extent to which the observed variables were correlated with the latent variable they belonged to. Regarding the five categories contributing to positive responses, the order according to their loadings was response efficiency (loading = 1), willingness and behavior (loading = 0.97), trust (loading = 0.85), cues to action (loading = 0.76), and knowledge (loading = 0.59). When we define 0.6 as the threshold value of loading, only knowledge was slightly below 0.6. The top-ranked response efficiency contained four questions about the effectiveness of self-protection, vaccination, quarantine, and distancing, suggesting belief in the effectiveness of NPIs and vaccination was most important to increase the compliance of NPIs among people. The following categories were willingness and behavior, as well as cues to action that were related to action, behavior, and recommendation of actions. Although among the four latent variables contributing to negative responses, the order according to their loadings was response efficiency (loading = 1), willingness and behavior (loading = 0.97), trust (loading = 0.85), cues to action (loading = 0.76), and knowledge (loading = 0.59). When we define 0.6 as the threshold value of loading, only knowledge was slightly below 0.6. The top-ranked response efficiency contained four questions about the effectiveness of self-protection, vaccination, quarantine, and distancing, suggesting belief in the effectiveness of NPIs and vaccination was most important to increase the compliance of NPIs among people. The following categories were willingness and behavior, as well as cues to action that were related to action, behavior, and recommendation of actions.
was a significant predictor of higher infection rates among certain groups. The questions of perceived barriers were about the difficulty to get protection appliances, vaccines, and worry about side-effects of vaccination. They were the common cause of vaccine hesitancy. As a previous study indicated, healthcare provider–related barriers and institutional barriers affected
preventive measures. Although the correlation network (Fig. 3) did not establish causation, it could provide proof to the following Bayesian network in terms of the link strength between nodes.

SEM analysis of latent variables and correlation network hereto did not tell the direction of effectiveness. In other words, the above technologies did not answer what factors had the most driving force and how they affected each other in a directed way. DAG produced by Bayesian network is a probabilistic graphical model with a direction, which represents a set of variables and their conditional dependencies. It can infer the likelihood of possible causes, which show the contributing strength to a status. This approach was used in identifying the most effective policy to control COVID-19 transmission. In the present study, the survey data of 34 questions were analyzed by Bayesian network method to derive the direction of action that shaped the population attitudes (Fig. 4). We reached several interesting conclusions from the findings of DAG analysis: mental depression and anxiety was an isolated factor staying clearly away. There were largely two primary effect paths with direction: the positive response path and the negative response way. The positive response path started from cues to action (Nodes 22, 23, and 21), to trust (Nodes 30, 28, and 29), to willingness and behavior (Nodes 6–8), and to response efficiency (Nodes 17, 19, and 20) and knowledge (10–12). This path revealed that cues to action were the driving force that directly affected trust and willingness and behavior, and subsequently, the affected two factors further influenced response efficiency and the last factor of knowledge. As to the negative response path that appeared in a simpler manner, it originated from perceived barriers (Nodes 15, 16, and 14) and moved to autonomy (Nodes 25–27). Meanwhile, threat had moderate linkage with one item of the last positive and negative categories. The primary application of the DAG was to suggest what factors should be the primary targets of government intervention. Upstream factors that were close to the top of the network, such as cues to action, should be the primary targets, as it appeared to be the source of activation driving. These findings imply that the critical point of increasing compliance with NPI and vaccination is to address the factors that locate at the beginning of Bayesian network, such as items of cues to action and perceived barriers. The items that show a direct link with willingness and behavior are also should be paid attention to.

Our study has several strengths and weaknesses. One aspect of strength is that our study was designed to systematically decipher the pros and cons of factors that influenced population’s attitudes from a broad scope of potential factors based on classical psychological theories. Another aspect of strength is the quantitative results that provide clues to the causal direction of the relationship between potential factors. The weak is that the demographic characteristics of participants might differ from other countries or in different stages of the pandemic. Second, the generalization of our findings to the general population is limited, as voluntary participation option and convenience sampling method may lead to selection bias. Another limitation is that people aged beyond 70 years are not included in this study, which requires a special study to investigate these people, as they may have different pros and cons factors toward their attitude. Yet, by classifying people into three age groups, we demonstrated that the age affects few aspects of factors. Moreover, the analysis procedure gains light to how to decipher the pros and cons of

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**Fig. 3.** Polychoric correlation network of 34 items in nine categories.
Fig. 4. Bayesian network of 34 items in nine categories. Note: the group color is the same with that in Fig. 3.
factors that influence population attitudes toward NPIs and vaccination during post–COVID-19.

Conclusion

To summarize, the present study successfully creates a panel of 34 questionnaire items that can be used to investigate the pros and cons attitudes toward NPIs and vaccination for COVID-19 prevention. The study unravels that response efficiency, willingness and behavior, cues to action, trust, and knowledge contribute to positive responses, whereas autonomy, perceived barriers, mental, and threat contribute to negative responses. Bayesian network analysis suggests that factors located near the top of the DAG of Bayesian network, such as cues to action and perceived barriers, should be addressed with a priority to efficiently increase the compliance with NPIs and vaccination.

Author statements

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Ethical approval

The protocol has been approved by the ethics committee of Ningbo University School of Medicine (approval number: NBU-2021-066).

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Competing interests

None to declare.

Author contributions

Q.S. designed the study, analyzed the data, and wrote the article. L.R. wrote the article and designed the questions. Y.M. provided the fund and revised the article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.puhe.2022.07.010.

References

1. Salyer SJ, Maeda J, Sembuche S, Kebede Y, Thangalala A, Moussif M, et al. The first and second waves of the COVID-19 pandemic in Africa: a cross-sectional study. Lancet 2021; 397(10281):1265–75. https://doi.org/10.1016/S0140-6736(21)00632-2.

2. Schoenbaum M, Colge L. Challenges to behavioral health and injury surveillance during the COVID-19 pandemic. JAMA Psychiatry 2021;78(3):924–5. https://doi.org/10.1001/jamapsychiatry.2021.1201.

3. Ding X, Brazel DM, Mills MC. Factors affecting adherence to non-pharmaceutical interventions for COVID-19 infections in the first year of the pandemic in the UK. BMJ Open 2021;11(10):e054200. https://doi.org/10.1136/bmjopen-2021-054200.

4. Organization. WH. Overview of public health and social measures in the context of COVID-19: interim guidance. 2020. Available: https://apps.who.int/iris/handle/10665/332115.

5. Li Y, Liang J, Gao L, Ayaz Ahmed M, Uy JP, Cheng C, et al. Face masks to prevent transmission of COVID-19: a systematic review and meta-analysis. Am J Infect Control 2021;49(7):900–6. https://doi.org/10.1016/j.ajic.2020.12.007.

6. Haug N, Gehrhofer L, Londei A, Dervic E, Desvars-Larrive A, Loreto V, et al. Ranking the effectiveness of worldwide COVID-19 government interventions. Nat Hum Behav 2020;4(12):1303–12. https://doi.org/10.1038/s41562-020-01009-0.

7. Alley SJ, Stanton R, Browne M, To QC, Khalesi S, Williams SL, et al. As the pandemic progresses, how does willingness to vaccinate against COVID-19 evolve? Int J Environ Res Public Health 2021;18(2). https://doi.org/10.3390/ijerph18020797.

8. Wong MCS, Wong ELY, Huang J, Cheung AWL, Law K, Chong MKC, et al. Acceptance of the COVID-19 vaccine based on the health belief model: a population-based survey in Hong Kong. Vaccine 2021;39(7):1148–56. https://doi.org/10.1016/j.vaccine.2020.12.083.

9. Babore A, Lombardi L, Viceconti ML, Pignataro S, Marino V, Crudele M, et al. Psychological effects of the COVID-19 pandemic: perceived stress and coping strategies among healthcare professionals. Psychiatr Res 2020;293:113366. https://doi.org/10.1016/j.psychres.2020.113366.

10. Kowsalski RM, Black JK. Protection motivation and the COVID-19 virus. Health Commun 2021;36(1):15–22. https://doi.org/10.1080/10410236.2019.1684746.

11. Saloni D, Conway MW, Capasso da Silva D, Chauhan RS, Derrible S, Mohammadan AK, et al. The potential stickiness of pandemic-induced behavior changes in the United States. Proc Natl Acad Sci U S A 2021;118(27). https://doi.org/10.1073/pnas.2010499118.

12. Schu S, Conner M, Wulffing S, Alhawat R, Prestwich A, Norman P. Do socio-structural factors moderate the effects of health cognitions on COVID-19 protection behaviours? Soc Sci Med 2021;285:114261. https://doi.org/10.1016/j.socscimed.2021.114261.

13. Halliday TJ, Mazumder B, Wong A. The intergenerational transmission of health in the United States: a latent variables analysis. Health Econ 2020;29(3):367–81. https://doi.org/10.1002/hec.3988.

14. Tarka P. An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. Qual Psychol 2018;52(1):313–54. https://doi.org/10.11135/0171-0694-8.

15. McNally RJ, Mair F, Mugno BL, Riemann BC. Morbid-obssive-compulsive disorder and depression: a Bayesian network approach. Psychol Med 2017;47(7):1204–14. https://doi.org/10.1017/s0033291716003287.

16. Ferreira S, Campos C, Marinho B, Rocha S, Fonseca-Pedrero E, Barbosa Rocha N. What drives beliefs in COVID-19 conspiracy theories? The role of psychotic-like experiences and confinement-related factors. Soc Sci Med 2021;292:114611. https://doi.org/10.1016/j.socscimed.2021.114611.

17. Lowe B, Kroenke K, Herzog W, Grafe K. Measuring depression outcome with a brief self-report instrument: sensitivity to change of the Patient Health Questionnaire (PHQ-9). J Affect Disord 2004;81(1):61–6. https://doi.org/10.1016/S0165-0327(03)00198-8.

18. Plummer F, Manea L, Trepel D, McMillan D. Screening for anxiety disorders with the GAD-7 and GAD-2: a systematic review and diagnostic metaanalysis. Gen Hosp Psychiatry 2016;39:24–31. https://doi.org/10.1016/j.genhosppsych.2015.11.005.

19. Jebb AT, Ng V, Tay L. A review of key Likert scale development advances: 1995-2019. Front Psychol 2021;12:637547. https://doi.org/10.3389/fpsyg.2021.637547.

20. Sijsma K. On the use, the misuse, and the very limited usefulness of Cronbach’s alpha. Psychometrika 2009;74(1):1107–20. https://doi.org/10.1007/s11336-008-9101-0.

21. Schou AE, Monteiro PL, Nunes AS. Factor structure of the convergence in sufficiency survey symptom questionnaire. PLoS One 2020;15(2):e0229511. https://doi.org/10.1371/journal.pone.0229511.

22. Epksip Sam semPlt. Unified visualizations of structural equation models. Struct Equ Model: A Multidiscip J 2015;22:474–83. https://doi.org/10.1177/1094402715593971.

23. W R. psych: Procedures for Psychological, Psychometric, and Personality Research. Northwestern University, Evanston, Illinois. R package version 2.1.9, https://CRAN.R-project.org/package=psych. 2021. https://doi.org/10.1007/s11336-008-9101-0.

24. Epksip Sam, Cramer AO, Waldorp LJ, Borsboom D. Graphical lasso estimation of Gaussian graphical models. R package version 1.8. https://CRAN.R-project.org/package=glasso. 2014.

25. Scutari M. Learning Bayesian networks with the bnlearn R package. 2009.

26. Jones RH. Bayesian information criterion for longitudinal and clustered data. Stat Med 2011;30(25):3050–6. https://doi.org/10.1002/sim.4323.

27. Sachs K, Perez O, Pe’er D, Lauffenburger DA, Nolan GP, Causal protein–signaling networks derived from multiparameter single-cell data. Science 2005;308(5721):523–9. https://doi.org/10.1126/science.1105809.

28. Krepis S, Prasad S, Brownstein JS, Hsven Y, Garibaldi BT, Zhang B, et al. Factors associated with US adults’ likelihood of accepting COVID-19 vaccination. JAMA Netw Open 2020;3(10):e2025594. https://doi.org/10.1001/jamanetworkopen.2020.25594.

29. Soveri A, Karlsson LC, Antfolk J, Lindfelt M, Lewandowsky S. Unwillingness to engage in behaviors that protect against COVID-19: the role of conspiracy beliefs, trust, and endorsement of conspiracy and alternative medicine. BMC Public Health 2021;21(1):684. https://doi.org/10.1186/s12889-021-10643-w.

30. Epksip Sam, Rhemtulla M, Borsboom D. Generalized network psychometrics: combining network and latent variable models. Psychometrika 2017;82(4):904–27. https://doi.org/10.1007/s11336-017-9557-x.
32. Borsboom D, Mellenbergh GJ, van Heerden J. The theoretical status of latent variables. *Psychol Rev* 2003;110(2):203–19. https://doi.org/10.1037/0033-295X.110.2.203.

33. Sandman I, Granger BB, Ekman I, Munthe C. Adherence, shared decision-making and patient autonomy. *Med Health Care Philos* 2012;15(2):115–27. https://doi.org/10.1007/s11019-011-9336-x.

34. Mersha A, Shibiru S, Girma M, Ayele G, Bante A, Kassa M, et al. Perceived barriers to the practice of preventive measures for COVID-19 pandemic among health professionals in public health facilities of the Gamo zone, southern Ethiopia: a phenomenological study. *BMC Publ Health* 2021;21(1):199. https://doi.org/10.1186/s12889-021-10256-3.

35. Serena H, Chen CAP. Good practice in Bayesian network modelling. *Environ Model Software* 2012;37:134–45.

36. Wibbens PD, Koo WW, McGahan AM. Which COVID policies are most effective? A Bayesian analysis of COVID-19 by jurisdiction. *PLoS One* 2020;15(12):e0244177. https://doi.org/10.1371/journal.pone.0244177.