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Original Research

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

Qifa Song [a, d], Yuwei Mi [b, d], Liemin Ruan [c, *]

[a] *Medical Data Center, Ningbo City First Hospital, Ningbo, Zhejiang Province, China*
[b] *School of Medicine, Ningbo University, Ningbo, Zhejiang Province, China*
[c] *Department of Psychosomatic Medicine, Ningbo City First Hospital, Ningbo University, Ningbo, Zhejiang Province, China*

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A B S T R A C T

Objectives: Population compliance greatly influences the effectiveness of vaccination and non-pharmaceutical interventions (NPIs) for the curtaining 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.

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.[1] Infectious diseases and human behaviors are generally intertwined. People's movements and interactions are the engines of transmission.[2] The COVID-19 pandemic has significantly changed our daily activities, which in turn greatly influence the development of the pandemic.[3] 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.[4,5] Vaccines are also given high expectations to effectively contain the pandemic. However, these measures have resulted in the significant impairment of physical and psychosocial well-being of people. Such impairment and 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.[6,7]

Earlier studies have identified a few underlying factors that might influence population compliance with NPIs and vaccination

* Corresponding author. Ningbo City First Hospital, Ningbo, Zhejiang Province, China.
E-mail address: lmruan@tom.com (L. Ruan).
[d] These authors contributed equally to this article.

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through questionnaire surveys designed on the basis of several psychological theories, such as health belief model,[8] perceived stress,[9] protection motivation theory,[10] theory of planned behavior,[11] as well as sociodemographic factors.[12] 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.[13] 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,[14] 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.[15]

People were reported to display varied overall attitudes toward vaccination and NPIs for the prevention of COVID pandemic;[16] 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;[8] threat assessment of COVID-19 and response efficiency based on the protection motivation theory;[10] as well as cues to action, and willingness and behavior based on the theory of planned behavior.[11] 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 Questionaire (PHQ-2) and 2-item Generalized Anxiety Disorder (GAD-2) were 4-point (0–3) scales,[17,18] 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.[19] 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.[20] The sampling adequacy for factor analyses was verified using Kaiser–Meyer–Olkin test (at least >0.7).[21] 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.[22] 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[23] to compute the polychoric correlation network and the qgraph R package to demonstrate the network.[24] The qgraph package produced regularized partial correlations using the lasso method by the glasso R package.[25] 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.[26] 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]).[27] 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.[28] 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 questionnaire items were defined and grouped into nine categories, which 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.

Table 1
Demographic characteristics.

Feature	Number (percentage)
Sample number	1700
Sex	
Female	842 (49.5)
Male	858 (50.5)
Marriage	
Married	1046 (61.5)
Unmarried	654 (38.5)
Age	
18–29 years	614 (36.1)
30–50 years	818 (48.1)
>50 years	268 (15.8)
Education level	
College and over	1276 (75)
Bellow college	424 (25)
Job status	
Medical staff	233 (13.7)
Other employed	1070 (62.9)
Retired	53 (3.1)
Student	187 (11)
Unemployed	157 (9.2)
Income (Chinese yuan/month)	
<4000	338 (19.9)
4000–8000	685 (40.3)
≥8000	677 (39.8)
Residence	
Urban	1380 (81.2)
Rural	320 (18.8)

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 represented the correlation magnitude. The number of edges linking a node 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

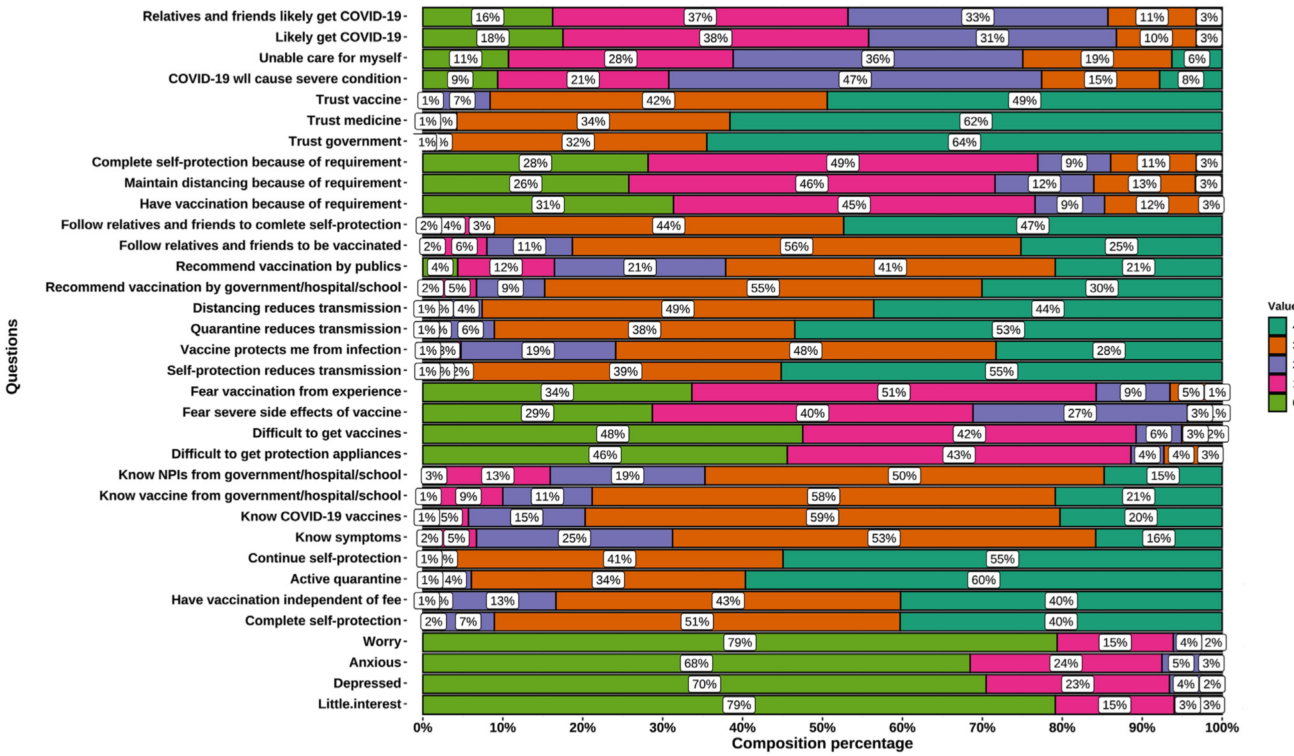

Fig. 1. Composition percentages of answers to 34 questions among 1700 respondents. Note: Except for four mental items are 4-point scale, ranging from 0 to 3, and the other items are 5-point scale, ranging from 0 to 4.

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 n'ot 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, autonomy (loading = 0.94) and perceived barriers (loading = 0.90) had the evident negative effectiveness as indicated by loadings. Autonomy can be defined as the ability of a person to make his or her own decisions. This faith in autonomy is the central premise of the concept of informed consent and shared decision-making.[33] This result proved that respect for people's decision-making rights deeply affected their adherence. Preceding literature described that autonomy leading to inability to abide by NPIs

Table 2
Likert scores of survey questions stratified by three age groups.

Questions	Age group			
	18–29	30–50	>50	Overall *P*
	***N* = 614**	***N* = 818**	***N* = 268**	
Little interest	0.36 (0.70)	0.29 (0.67)	0.15 (0.47)	<0.001[a]
Depressed	0.46 (0.71)	0.39 (0.70)	0.22 (0.54)	<0.001[a]
Anxious	0.49 (0.76)	0.43 (0.72)	0.22 (0.51)	<0.001[a]
Worry	0.34 (0.69)	0.29 (0.65)	0.16 (0.48)	0.001[a]
Complete self-protection	3.29 (0.71)	3.29 (0.72)	3.27 (0.66)	0.893
Have vaccination independent of fee	3.18 (0.87)	3.20 (0.82)	3.18 (0.74)	0.862
Active quarantine	3.51 (0.70)	3.52 (0.66)	3.52 (0.61)	0.987
Continue self-protection	3.51 (0.62)	3.50 (0.66)	3.41 (0.59)	0.058
Know symptoms	2.77 (0.84)	2.80 (0.82)	2.63 (0.86)	0.011[a]
Know COVID-19 vaccines	2.96 (0.78)	2.94 (0.80)	2.84 (0.79)	0.119
Know vaccine from government/hospital/school	2.94 (0.85)	2.89 (0.90)	2.74 (0.88)	0.007[a]
Know NPIs from government/hospital/school	2.58 (0.96)	2.58 (1.00)	2.74 (0.96)	0.057
Difficult to get protection appliances	0.73 (0.92)	0.76 (0.94)	0.82 (0.96)	0.484
Difficult to get vaccines	0.70 (0.88)	0.72 (0.85)	0.65 (0.78)	0.582
Fear severe side-effects of vaccine	1.05 (0.91)	1.11 (0.88)	1.07 (0.84)	0.454
Fear vaccination from experience	0.87 (0.88)	0.91 (0.86)	0.91 (0.84)	0.613
Self-protection reduces transmission	3.43 (0.81)	3.46 (0.77)	3.43 (0.60)	0.753
Vaccine protects me from infection	2.94 (0.93)	3.00 (0.85)	3.03 (0.70)	0.256
Quarantine reduces transmission	3.40 (0.79)	3.43 (0.76)	3.37 (0.76)	0.491
Distancing reduces transmission	3.25 (0.83)	3.36 (0.72)	3.34 (0.63)	0.023[a]
Recommend vaccination by government/hospital/school	3.03 (0.92)	3.09 (0.84)	3.04 (0.82)	0.347
Recommend vaccination by publics	2.60 (1.08)	2.68 (1.07)	2.50 (1.07)	0.054
Follow relatives and friends to be vaccinated	2.97 (0.92)	2.98 (0.88)	2.88 (0.87)	0.272
Follow relatives and friends to complete self-protection	3.36 (0.81)	3.32 (0.87)	3.17 (0.87)	0.009[a]
Have vaccination because of requirement	1.03 (1.06)	1.12 (1.04)	1.16 (1.08)	0.117
Maintain distancing because of requirement	1.12 (1.00)	1.24 (1.10)	1.39 (1.12)	0.002[a]
Complete self-protection because of requirement	1.02 (0.94)	1.08 (1.05)	1.46 (1.17)	<0.001[a]
Trust government	3.59 (0.61)	3.60 (0.60)	3.62 (0.55)	0.715
Trust medicine	3.55 (0.65)	3.56 (0.61)	3.57 (0.60)	0.932
Trust vaccine	3.43 (0.69)	3.37 (0.73)	3.36 (0.64)	0.218
COVID-19 causes severe condition	1.92 (1.04)	1.88 (1.01)	1.93 (0.99)	0.703
Unable care for myself	1.79 (1.06)	1.82 (1.06)	1.86 (1.05)	0.692
Likely get COVID-19	1.31 (0.99)	1.45 (0.98)	1.64 (1.03)	<0.001[a]
Relatives and friends likely get COVID-19	1.41 (1.03)	1.50 (0.98)	1.59 (0.96)	0.049[a]

The Likert scores are expressed in mean (SD).
[a] Likert scores are statistically different among three groups.

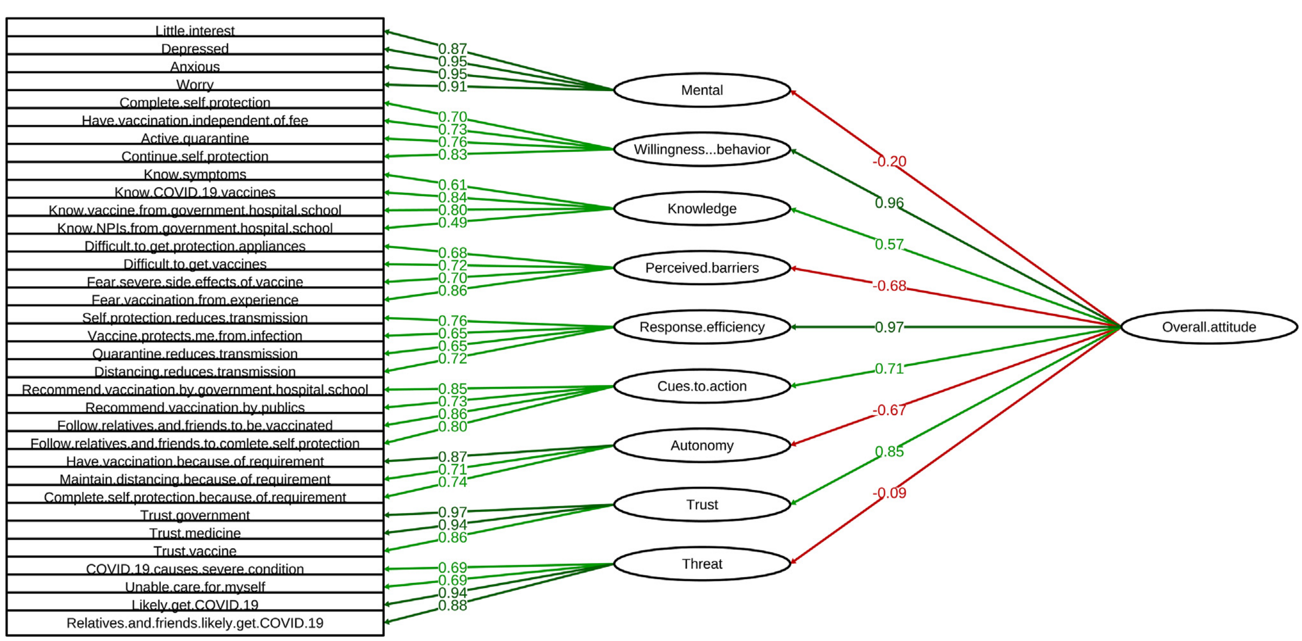

Fig. 2. SEM illustrates the framework of 34-item instrument including nine latent variables.

was a significant predictor of higher infection rates among certain groups.[3] 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

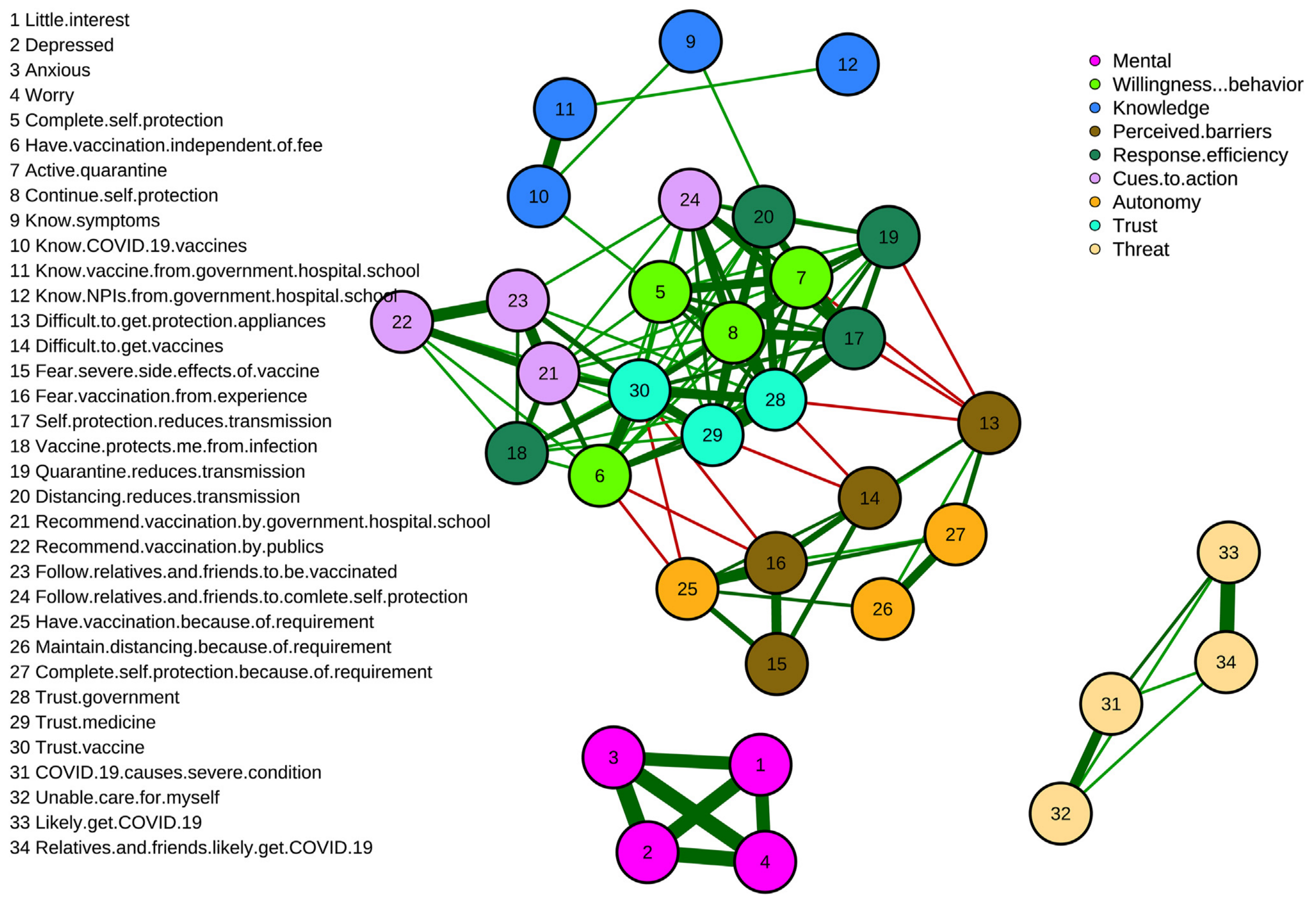

Fig. 3. Polychoric correlation network of 34 items in nine categories.

preventive measures.[34] Although the correlation network (Fig. 3) did n'ot 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 n'ot tell the direction of effectiveness. In other words, the above technologies did n'ot 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.[35] 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.[36] 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

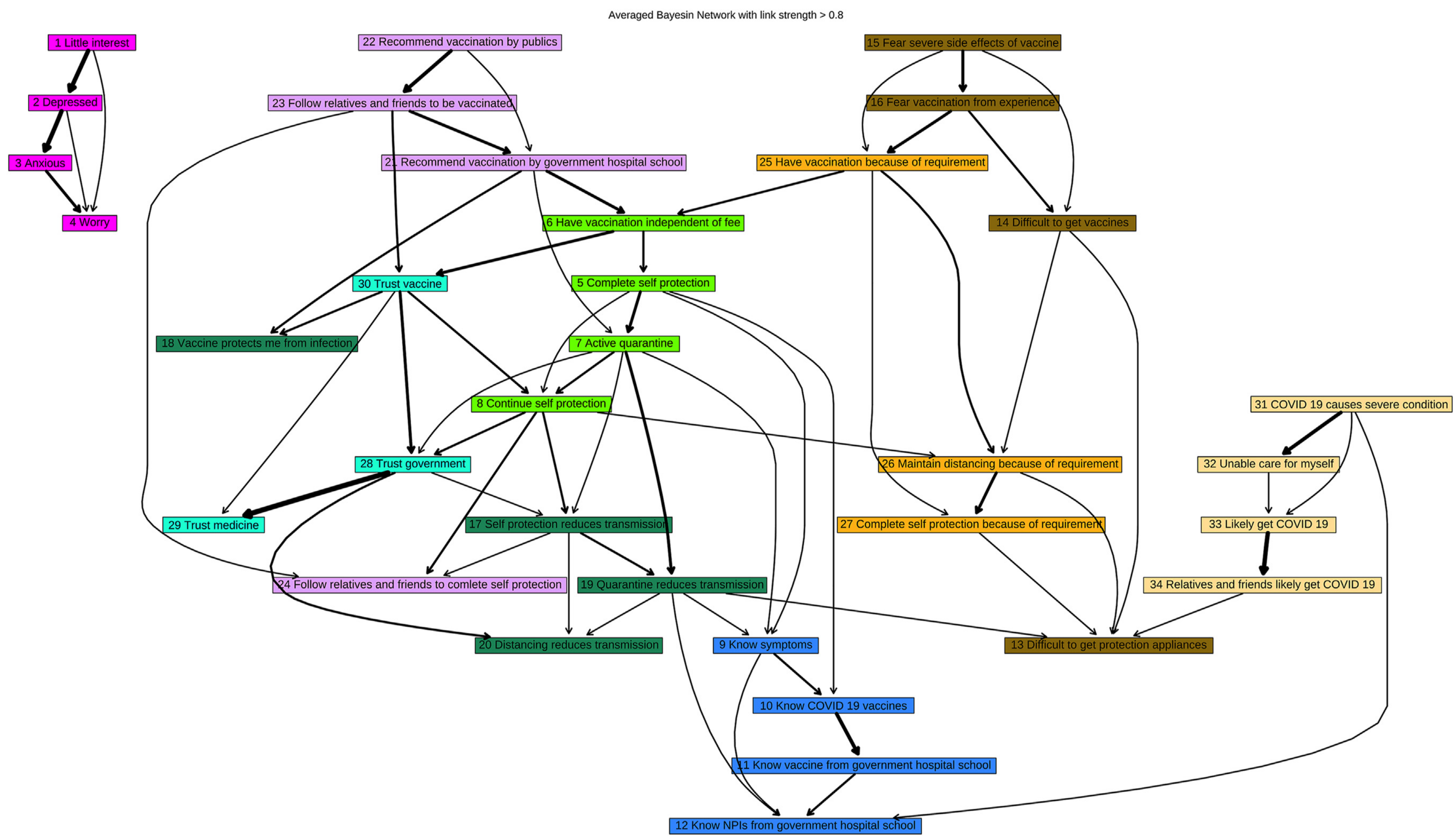

Fig. 4. Bayesian network of 34 items in nine categories. Note: the group color is the same with that in Fig. 3.

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. Y.M. wrote the article and designed the questions. L.R. 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.

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