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Trust, risk perception, and COVID-19 infections: Evidence from multilevel analyses of combined original dataset in China☆

Maoxin Ye[a], Zeyu Lyu[b,*]

[a] Department of Sociology, School of Humanities, Southeast University, 2 Southeast University Road, Jiangning District, Nanjing 211189, P.R. China
[b] Graduate School of Arts and Letters, Tohoku University, 27-1 Kawauchi, Aoba-ku, Sendai, 980-8576, Japan

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ABSTRACT

Previous studies have revealed medical, democratic, and political factors altering responses to unexpected infectious diseases. However, few studies have attempted to explore the factors affecting disease infection from a social perspective. Here, we argue that trust, which plays an important role in shaping people' s risk perception toward hazards, can also affect risk perception toward infections from a social perspective. Drawing on the indication that risk perception of diseases helps prevent people from being infected by promoting responsible behaviors, it can be further asserted that trust may alter the infection rate of diseases as a result of risk perception toward infectious diseases. This is an essential point for preventing the spread of infectious diseases and should be demonstrated. To empirically test this prediction, this study uses the COVID-19 outbreak in China as an example and applies an original dataset combining real-time big data, official data, and social survey data from 317 cities in 31 Chinese provinces to demonstrate whether trust influences the infection rate of diseases. Multilevel regression analyses reveal three main results: (1) trust in local government and media helps to reduce the infection rate of diseases; (2) generalized trust promotes a higher rather than lower infection rate; and (3) the effects of different types of trust are either completely or partly mediated by risk perception toward diseases. The theoretical and practical implications of this study provide suggestions for improving the public health system in response to possible infectious diseases.

Credit author statement

Maoxin Ye: Conceptualization, Methodology, Formal analysis, Writing - original draft; Zeyu Lyu: Data curation, Writing - review & editing, Visualization

1. Introduction

Since the 2000s, the world has experienced several outbreaks of infectious diseases, including Severe Acute Respiratory Syndrome (SARS), H1N1, and Ebola, that have not only caused several deaths but also led to wide-ranging and long-term socioeconomic disruptions (Fonkwo, 2008; Huber et al., 2018).

In December 2019, a new cluster of pneumonia cases identified as the coronavirus disease 2019 (COVID-19) emerged in Wuhan, and the infection quickly spread throughout China and the world. By April 22, 2020, this pandemic had already infected more than 84,000 individuals and caused over 4600 deaths in China. Globally, it had infected 2.5 million people and caused over 178,000 deaths in the same time. According to the National Bureau of Statistics of China (2020), the first quarter gross domestic product (GDP) in China was 6.8% lower than that in last year, which has been extremely rare after the implementation of the reform and opening-up policy.

Considering that infectious disease represents a considerable threat to society, for a better and more urgent response during such a public health crisis, beyond efforts in medicine, further empirical studies are needed to investigate what social factors can determine the spread of disease.

In the case of COVID-19 in China, it was indicated that citizens' trust in institutions was related to compliance with government regulations, including travel restrictions and social distancing. This cooperation effectively prevented the spread of COVID-19 within China (Wang 2020; World Economic Forum 2020), suggesting the importance of trust in preventing the spread of infectious diseases. However, no previous

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* Corresponding author.
E-mail addresses: ye_maoxin@seu.edu.cn (M. Ye), lyu.zeyu.r8@dc.tohoku.ac.jp (Z. Lyu).

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studies have empirically explained the connection between trust and the spread of infectious diseases. In order to bridge this research gap, the current study aims to comprehensively describe how people's trust influences the spread of infectious diseases.

By using the spread of COVID-19 in China as a focused case and applying an original dataset combining real-time big data, official data, and social survey data, this study explores the influence of trust on COVID-19 infection. Additionally, we treat risk perception of diseases as a mediating variable to explain the relationship between trust and infections.

2. Literature review

2.1. Trust, risk perception, and infection rate

Previous studies have suggested that risk perception or preventive behaviors toward a specific infectious disease directly reduce the infection rate (Lau et al. 2003, 2004; Rvachev and Longini 1985; Weston et al., 2018). For instance, being risk-averse, wearing masks, washing hands, and staying at home were found to have protective effects against SARS and H1N1 infections. Accordingly, whether the infection rate increases or decreases depends on the degree of people's risk perception or preventive behaviors toward that infectious disease.

Previous studies have demonstrated that trust is the most crucial factor affecting people's risk perception of a specific hazard (Siegrist et al., 2005; Smith and Adam, 2018). Since infectious diseases are a hazard to society, trust may also influence risk perception toward diseases. In this sense, this study utilizes the theories applied in previous studies on risk management to interpret the relationship between trust and risk perception toward diseases.

Research on risk management revealed that trust could be largely categorized as social and generalized trust (Siegrist 2019). Social trust refers to trust in those "whom people do not personally know or on institutions responsible for regulating or handling certain hazards" (Siegrist 2019: p. 4). Additionally, in social trust, trust in the government and media are the most important aspects because they are the origin of the spread of information concerning the risks (Siegrist et al., 2000). In this sense, trust in governments and media can be considered the main types of social trust, and they are applied separately in this study.

Generalized trust refers to the differing characteristics between individuals with regard to their willingness to trust other members of society in general (Inglehart 1997; Paxton 2007; Putnam 1995; Verba et al., 1995); it is also a crucial part of social capital (Putnam 2000). Generalized trust is deemed an optimistic trait within that person (Siegrist 2019), which is essential to people's risk perception in risk management. Because it is also a crucial factor affecting people's risk perception, it is applied in this study.

2.2. Trust in government and media, risk perception, and infection rate

Numerous previous studies have discussed the relationship between social trust and risk perception in risk management, revealing that judging the risk of hazards requires knowledge about these hazards. When people lack knowledge, they must rely on trusted institutions to assess the risk of hazards (Earle and Cvetkovich, 1995; Luhmann, 1989). Here, the *similarity heuristic* is emphasized as the mechanism between social trust and risk perception.

The similarity heuristic alters people's judgment toward the risk of hazards in two aspects that make up Earle and Cvetkovich's *salient value similarity (SVS)* model (1995). The first is salient values, implying that when judging the risk of hazards, assigning a value to the hazards becomes salient (Earle and Cvetkovich, 1995; Siegrist et al., 2000). The second is value similarity, in which people determine the trustworthiness of institutions by assessing the risk of hazards using the similarity of the salient values of other people or institutions (Earle, 2010; Earle and Cvetkovich, 1995; Siegrist et al., 2000).

Since SVS is highly related to trust (Earle and Cvetkovich 1999), having a higher level of trust in the institutions means sharing similar values with them; thus, the information or attitude of those institutions toward an issue or hazard will have a greater effect on our assessment, that is, perception of risk toward that same issue or hazard. This way, trust can affect people's risk perception.

Previous studies have proposed a comprehensive model named the *trust, confidence, and cooperation (TCC) model* (Earle 2010; Earle and Siegrist 2008; Earle et al., 2007). This model contends that people trust in institutions, assuming cooperating behaviors in dealing with the hazards.

Since infectious diseases are categorized as a type of hazard, a heuristic effect may be appropriate to interpret the relationship between social trust and risk perception of infectious diseases; in other words, social trust affects people's risk perception toward infectious diseases through the heuristic effect of institutions sharing the same values with them.

Infectious diseases are public hazards to both governments and people. The responsibility of the government in dealing with diseases comes from reducing the impact that will influence people's lives. In this sense, governments attempt to provide information concerning preventive behaviors, such as wearing masks and washing hands, to enhance people's risk perception. Therefore, people who trust more in the government are more likely to cooperate, having a higher level of risk perception toward the diseases and engaging in preventive behaviors. As mentioned above, since risk perception and preventive behaviors can effectively decrease the infection rate, trust in government may reduce the infection rate of the diseases. Moreover, because the influence of trust in government on the infection rate is through risk perception toward the diseases, risk perception will mediate the relationship between trust in government and the infection rate.

Previous studies have also indicated that trust in different levels of governments has different effects on risk perception toward the same issue. Ma and Christensen (2018) suggested that trust in the local government has a greater impact on people's risk perception than trust in the central government. They believe that "central government addresses general policies and guidelines for crisis management and only becomes involved when crises escalate and go beyond the scope of specific jurisdictions, while in most cases it is local governments that response to and handle crises" (Ma and Christensen, 2018: p. 5). Thus, the policies taken by the local governments, rather than the central government, are more likely to be evaluated by the citizens living in the area. In other words, local governments have a higher level of heuristic effect on people's attitudes than does the central government. From this perspective, trust in the local government may have a greater effect on decreasing the infection rate than does trust in the central government.

Regarding trust in the media, Kasperson et al. (1988) mentioned that the frequency of media usage is positively associated with risk perception; in other words, media usage improves people's risk perception. The *social amplification of risk framework* (SARF) is proposed to interpret this result (Kasperson et al., 1988), indicating that information will be simplified by the media during transmission, and the signal of the information, such as risk, will be emphasized while other contents will be ignored. Therefore, people who use media more frequently are more likely to receive simplified information and have a higher level of risk perception.

Combining this framework with the heuristic effect, the purpose of the media is to transmit information and, since the media amplifies the risks, people who trust in the media are more likely to have a higher level of risk perception toward hazards, including diseases, and engage in preventive behaviors. Thus, trust in the media may also decrease the infection rate. Since the influence of trust in the media on the infection rate is through risk perception toward diseases, risk perception will mediate the relationship between trust in the media and the infection rate.

Trust in the media can also be divided into trust in local and central media. Central media is more likely to provide information related to the entire county rather than local areas; this kind of information shares less similar values for people living in different areas. Accordingly, trust in central media may have a smaller effect on people's risk perception. Local media publishes information that is close to people; thus, it shares more common values with people and has a greater heuristic effect on their risk perception. Accordingly, trust in local media may have a greater effect on people's risk perception. Since risk perception can reduce the infection rate, trust in local media also has a greater impact on the infection rate than does trust in central media.

2.3. Generalized trust, risk perception, and infection rate

As mentioned above, generalized trust refers to the differing characteristics between individuals with regard to their willingness to trust other members of society in general (Inglehart 1997; Paxton 2007; Putnam 1995; Verba et al., 1995). This definition implies that people who have a higher level of generalized trust or, in other words, are more likely to unconditionally trust others, also have a higher level of optimism (Siegrist 2019). Because of this optimism, people are less likely to pay attention to the existing risk of hazards and have a lower level of risk perception (Siegrist 2019). Therefore, this optimistic trait decreases risk perception toward hazards.

Previous empirical studies concerning risk management have revealed that generalized trust is negatively associated with people's risk perception (Siegrist et al., 2005; Smith and Adam, 2018). Since infectious diseases are also a health hazard, people who have a higher level of generalized trust may also be optimistic toward diseases. Thus, generalized trust may reduce people's risk perception of infectious diseases. Given that risk perception helps to reduce the infection rate, generalized trust may increase the infection rate by decreasing risk perception.

However, another mechanism implies an adverse result in the relationship between generalized trust and risk perception. According to previous studies, generalized trust plays an important role linking institutions and people in the flow of information from official sources to individuals in a community, since it is also related to trust in institutions (Gilson 2003; Larson et al., 2018; Rothstein and Stolle 2008). In this sense, because trust in institutions is social trust, both the similarity heuristic and SARF mentioned above can be applied in generalized trust. The responsibility and purpose of institutions regarding infectious diseases decrease the infection rate, allowing institutions to transmit information about infection prevention to people. Additionally, in the process of transmission, the risk of the diseases is amplified by the information stations; therefore, people's risk perception toward infectious diseases will be promoted by trust in institutions in the community. Accordingly, generalized trust may also improve people's risk perception about diseases. Because risk perception can help to reduce the infection rate, generalized trust may also decrease it.

Although there may be two consequences of the relationship between generalized trust and infection rate, regardless of the mechanism, generalized trust influences the infection rate through its impact on the risk perception of diseases. Therefore, since the influence of generalized trust on the infection rate is through risk perception, risk perception may mediate the relationship between them.

3. Data and methods

3.1. Data

The dataset applied in this study comprised big data in real time, official data published by governments, and social survey data collected by the institutions. For data related to COVID-19, the number of daily confirmed COVID-19 cases in each city was utilized, and the cases were derived from the information published by the official websites of national, provincial, and municipal Health Commissions, which have been officially applied in several reports and scientific research (Jia et al., 2020; Lai et al., 2020; WHO 2020; Zhang et al., 2020).

Additionally, previous studies demonstrated that population outflow from Wuhan significantly determines the spread of COVID-19 in a certain district (Fan et al., 2020). To control its impact, population migration data were collected from the Baidu dataset (http://qianxi.baidu.com/), which provides the daily population migration scale from Wuhan and proportions of the destination provinces or cities. More specifically, the daily population outflow from Wuhan for each province or city was calculated by multiplying the daily outflow scale by the corresponding proportion for each province or city.

For the survey data, trust and risk perception toward diseases were collected from the *Chinese General Social Survey* (CGSS). This is the earliest and most comprehensive national representative continuous survey project run by academic institutions in China. The survey samples cover all provinces in China, excluding Hong Kong, Macau, and Taiwan, and are based on situations, such as population and economy, of each province in China; thus, the samples are representative of each province.

Since only CGSS2010 includes all the questions concerning social trust and risk perception toward infectious diseases, this was used for analyses. CGSS2010 was collected using the Stratified Multistage Random Sampling method from 31 provinces in China, targeting people over 18 years old; it contained 11,783 valid respondents, with a response rate of 74.31%.

It should be noted that although survey data is somewhat lacking in various timelines, the estimated variables at the province-aggregate level in the CGSS2010 allow us to approach the period under study for the following reasons. The Chinese government manages a population with a system of household registration called the *Hukou* system. Each Chinese citizen was identified as an agricultural or nonagricultural hukou and further categorized by location of origin. From the perspective of population movement, the *Hukou* system tied people to specific areas and thus restricted population movement (Ngai et al., 2019).

Previous studies have indicated that sociopolitical attitudes, including trust, are generally stable in adulthood (Sears and Funk 1999); moreover, there exists a similarity in sociopolitical attitude between parents and their children in terms of generation transmission (Jennings and Niemi 1978; Jennings et al., 2009). Taken together, since residents in a certain area of China should not change dramatically, and the trust of these residents and their next generation were generally stable, the aggregate-level of trust in a certain district should persist over a decade. Therefore, it is reasonable to assume that the observed trust in the CGSS2010 is still representative to some extent.

The official data at the city and provincial level were collected from the *Chinese City Statistical Yearbook* and the National Bureau of Statistics, respectively.

3.2. Measurements

Regarding the dependent variable, this study utilized the infection rate of COVID-19 at the city level for the analyses. It was calculated by dividing the cumulative number of confirmed infections (CNCI; including cured and deceased cases) on February 21 by the total population in each city. The equation for the calculation can be expressed as follows:

$$Infection\ Rate_{it} = log\left(\frac{CNCI_{it}}{Population_i} \times 10000 + 0.0005\right) \tag{1}$$

Fig. 1 illustrates the amount of daily newly confirmed cases of COVID-19 in Hubei Province and other provinces. As shown in Fig. 1, after February 21, there was no explosive growth of daily confirmed infections in any Chinese province except Hubei Province, and the CNCI on February 21 represents the total infections there. Thus, this study

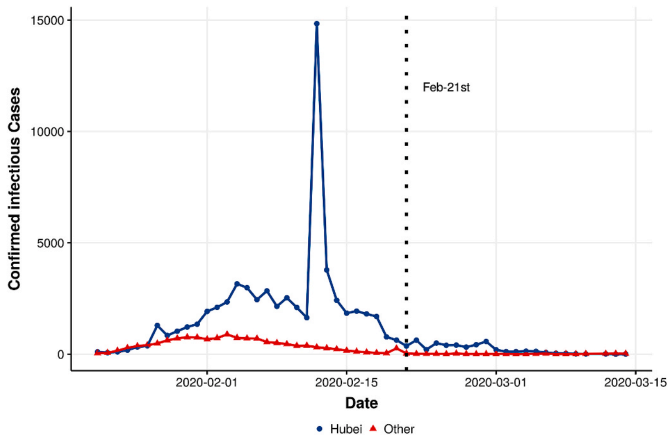

Fig. 1. Daily confirmed cases of COVID-19.

used the infection rate on February 21 as the dependent variable. Since the calculated infection rate is not normally distributed, to fit with the assumption of linear regression analysis, it was additionally taken as the logarithm after 0.0005.

Furthermore, in order to check the robustness of used CNCI data on February 21, we also utilize the CNCI on March 15, which is the day when the Chinese government announced the lifting of the emergency, and October 1, which is a more recent day, for the following regression analyses, and the regression results regarding these two infection rates are shown in Appendix 1 and 2.

With regard to the independent variables, as mentioned above, data were collected from the CGSS2010. Based on the measurement of trust used by previous studies (Edward et al., 2000), generalized trust was measured by question: “Generally speaking, do you agree that most people can be trusted in the society?” The answers ranged from “totally disagree” to “totally agree” on a scale with five choices. The inverted results of these scales were used for the analyses. Trust in central and local government and media were measured by the question: “What is your degree of trust in the institutions listed below: central government, local government, central media, and local media?” The answers ranged from “totally distrust” to “totally trust” on a scale with five choices for each object of interest.

This study used the degree of attention to the 2009 flu pandemic (H1N1) as the coping behavior of health risk as the mediating variable. The question posed to the respondents was: “What was your degree of attention to the 2009 flu pandemic?” The answers ranged from “not at all concerned” to “paid great attention to” on a scale with four choices. There are two reasons for using this question to measure coping behaviors to health risk. First, as mentioned by previous studies, the degree of attention to a public issue is the most basic approach to coping behaviors (Lindell and Perry 2012; Silver 2018). If people do not even pay attention to the issues, they are less likely to engage in coping behaviors to the risks they face.

Second, as emerging infectious diseases without vaccines at the time of their outbreak, COVID-19 and H1N1 influenza share several similarities regarding human-to-human transmission, common clinical symptoms, and the main route of transmission (Wang et al., 2020). Previous studies suggest that factors affecting individuals’ risk perception and protective behaviors are generally similar among infectious diseases such as SARS and H1N1 influenza (Park et al., 2010). From this perspective, even if the level of severity was different, we argue that risk perception of H1N1 influenza can predict the relative level of risk perception during the COVID-19 pandemic.

Because other variables may also influence the infection rate of COVID-19, especially the population flow from Wuhan, demographic, socioeconomic, and administrative variables are also included in the analyses (Fan et al., 2020; Ying et al., 2020). Demographic variables include population density and population flow from Wuhan at the city level, the proportion of elderly people, which is calculated by the ratio between people over 65 years old and the total population, and the average size of households at the province level. Socioeconomic variables include GDP per capita at the city level, average education year, and proportion of social insurance expenditure, which is calculated as the ratio between social insurance expenditure and total insurance expenditure, at the province level. The administrative variables include city type and Hubei Province at the city level. Controlling Hubei Province is because Wuhan, which is the epicenter of COVID-19, is the capital city of this province. The data before 2018 of these control variables were used for analyses. Detailed descriptive statistics of all variables are shown in Table 1. To easily understand the situation of infection rates in the cities, we added the variable of infection rate before taken log in Table 1. The mean was 0.583, meaning that on average, in each city, there were approximately 6 people per 100,000 infected by COVID-19.

3.3. *Analytical methods*

In this study because the variables are used at both the province and city levels, it is necessary to apply a multilevel approach. Thus, this study applied a multilevel regression model, as expressed by equation (2).

Level 1 (city-level)

$$IR_i = \beta_{oj} + \beta_{CVj}(CV)_{ij} + r_{ij} \tag{2}$$

Level 2 (province-level)

Table 1
Descriptive statistics of the variables.

Variables	Mean/ Percentage	Standard deviation	Min	Max
Dependent variables				
Infection rate	0.583	3.595	0.000	61.903
Infection rate (log)	−2.496	2.089	−9.903	4.126
Independent variables				
Trust in central government	4.444	0.212	3.960	4.930
Trust in local government	3.492	0.239	3.070	4.450
Trust in central media	4.141	0.243	3.650	4.860
Trust in local media	3.404	0.250	2.870	4.410
Generalized trust	3.404	0.250	2.780	4.410
Risk perception	3.448	0.168	2.73	3.68
Control variables				
Proportion of elderly people	0.117	0.022	0.072	0.152
Average education years	7.419	0.462	6.418	10.479
Unemployment rate	3.148	0.495	1.400	4.000
Average number of household persons	3.129	0.260	2.452	3.645
Proportion of social insurance expenditure	0.145	0.038	0.096	0.274
Population flow from Wuhan	0.020	0.076	0.000	0.824
Population density (ten thousand/ km2)	0.042	0.036	0.000	0.279
GDP per capita	59199.850	54603.620	10926.630	506301.300
City type				
Prefecture-level cities	81.700			
Central direct or province-capital cities	9.150			
County-level cities	9.150			
Hubei Province				
Other provinces	94.950			
Hubei Province	5.050			

City number: 317, Province number: 29.

$$\beta_{oj} = \gamma_{00} + \gamma_{01}(T)_j + \gamma_{02}(RB)_j + \mu_{0j}$$

$$\beta_{CVj} = \gamma_{CV0} + \mu_{CVj}$$

Level 1 in equation (2) is the estimation at the city level, which is the same as the Ordinary Least Squares (OLS) regression estimation, where IR_i is the infection rate at city i and β_{oj} is the intercept of regression at province j. $(CV)_{ij}$ is the vector of the control variables, and β_{CVj} represents the vector of their regression coefficients in province j. r_{ij} expresses the error term of regression.

According to the multilevel regression model, the intercept of the regression at the city level is determined by the factors at the province level. Thus, at Level 2, γ_{00} is the intercept at the ward level, $(T)_j$ and $(RB)_j$ represent trust and coping behavior to health risk, and γ_{01} and γ_{02} are their coefficients. μ_{0j} represents the error term of this regression. Because the regression coefficients at the individual level are also affected by the province level, the coefficients β_{CVj} of the control variables also have intercepts γ_{CV0} and error terms μ_{CVj} at the province level. Finally, through the estimation, we obtain the coefficients of the main independent variables, β_{Tj}, to establish how it affects the infection rate.

4. Results

Before evaluating the statistical analyses of the relationship between the types of trust and infection rate, to explore more details concerning the main variables, visualized geological maps of these variables are shown below.

Fig. 2 shows the distribution of the COVID-19 infection rate, risk perception toward infectious diseases, trust in local government, trust in local media, and generalized trust within the provinces of mainland China.

With regard to the infection rate, because the epicenter of this disease was Wuhan city, naturally, the infection rate of Hubei Province, showing the darkest color, was the highest. The infection rates of other provinces around Hubei were second highest. Infection rates in Qinghai and Xizang, which have the lightest color, were the lowest.

With regard to the distribution of risk perception toward infectious disease, the figure shows that Qinghai has the highest concern, while Hubei and the surrounding provinces have relatively lower levels of infection.

Because trust in local government and media may have a relatively greater impact on the infection rate compared with trust in central government and media, only the distribution of local government and media is shown here. Through the color of the figures, it can be confirmed that the level of trust in local government and media was extremely high in Xinjiang and Xizang. This could be because Xinjiang and Xizang both have a higher level of autonomy than do other provinces in mainland China, and people there are governed by those of their own ethnicity. Other provinces, including Hubei, have relatively lower levels of trust in both the local government and media.

Finally, with regard to the distribution of generalized trust, generally, most provinces, including Hubei, showed a higher level of generalized trust. Xinjiang and Xizang showed relatively lower levels of generalized trust.

Through the visualized geological maps of the main variables, it can be confirmed that Xinjiang and Xizang displayed extreme values for both dependent and independent variables. This point may cause an overestimation of the results in the following analyses. To show this problem, a visualized correlation between the main independent variables and infection rate at the province level was conducted, as shown below.

Fig. 3 shows the correlations between trust in local government, trust in local media, generalized trust, and infection rate. Xizang and Xinjiang indeed experience extreme effects on all these types of correlations because they are located in extreme positions in these figures. In this sense, if the following multilevel regression analyses included these two provinces, the results would have been overestimated. Thus, the analyses excluded Xizang and Xinjiang.

For the statistical analyses of multilevel regression, the results were divided into four main parts. The first confirmed whether the types of trust increase or decrease people's risk perception toward infectious diseases. The correlations among the main dependent and independent variables are presented in Table 2.

The second column of this table shows the correlation between risk perception and each type of trust. The results confirm that, except for trust in the central government, all types of trust are significantly ($p < 0.05$) associated with risk perception. However, regarding the coefficients, generalized trust is negatively associated (−0.322) with risk perception, while trust in local government, central media, and local media is positively associated (0.333, 0.152, and 0.355, respectively).

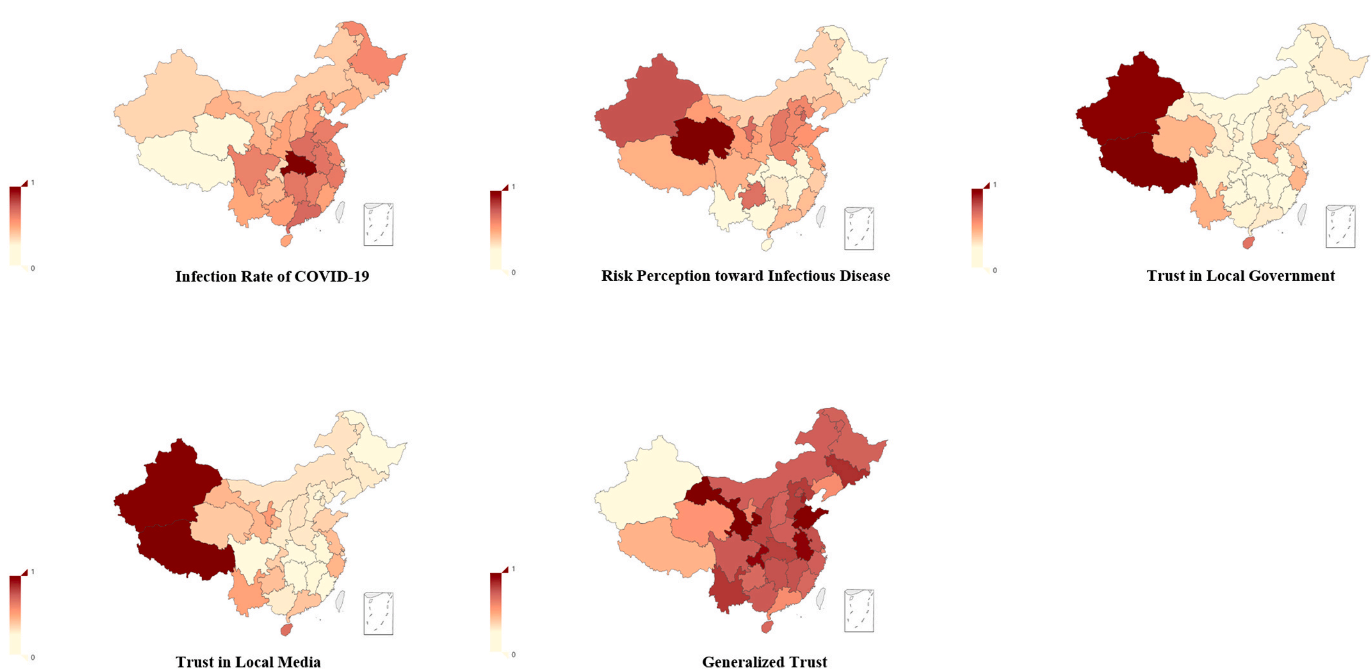

Fig. 2. Distribution of dependent, independent, and mediating variables. Note: Values in each figure were normalized to the 0–1 range.

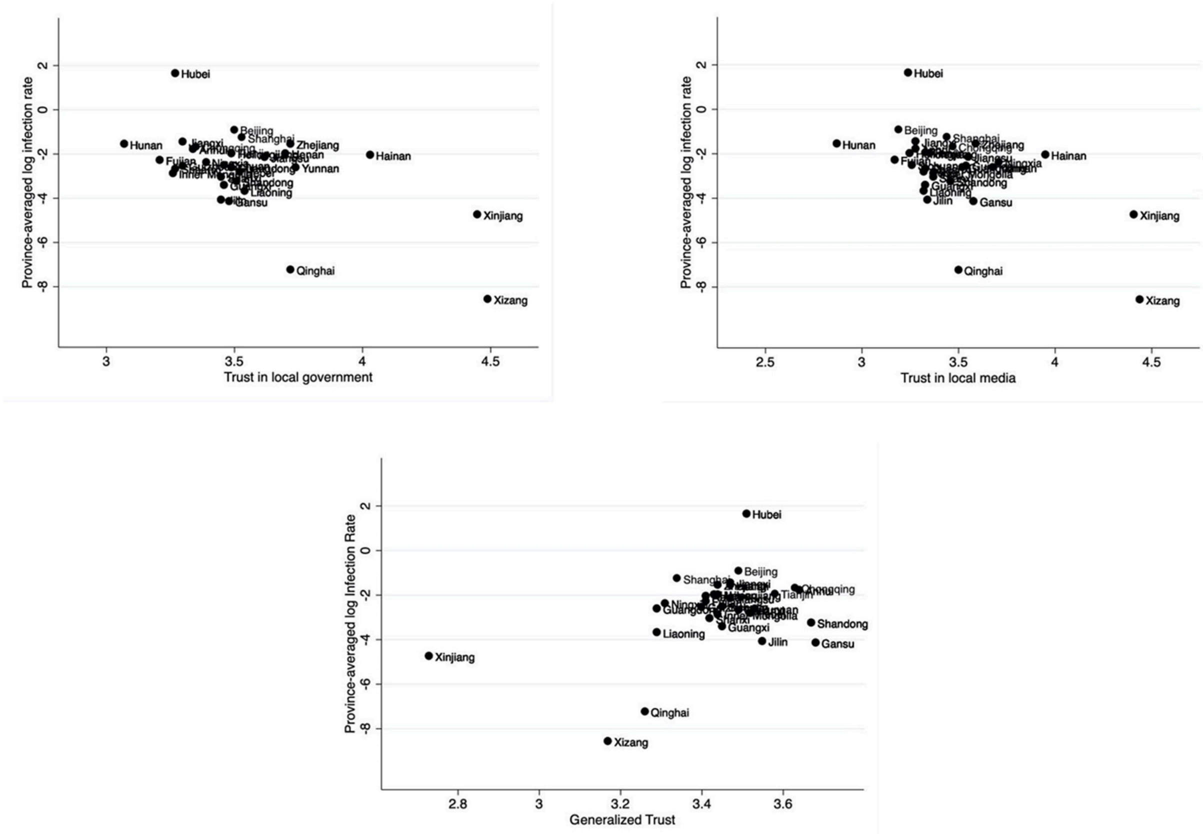

Fig. 3. Correlations between trust and infection rate.

These results suggest that generalized trust reduces people's risk perception, while social trust induces it. How do these results affect the infection rate? The following results answer this question.

The second part demonstrates the relationship between trust in central and local governments and the infection rate. The results are shown in Table 3.

Two models are listed in this table. In Model 1, trust in the central and local governments are included, but the results show that trust in the central government is not significantly associated with the infection rate ($\beta = -1.206$, n.s.), while trust in local government is negatively and significantly associated with it ($\beta = -1.817$, $p < 0.05$). The results indicate that trust in the central government has no effect on the infection rate, while trust in the local government helps decrease it. In Model 2, when risk perception is included, the coefficient of trust in local government becomes non-significant ($\beta = -1.194$, n.s.). According to the results in Table 2, trust in local government was significantly and positively associated with risk perception. In addition, in Table 3, risk perception is negatively associated with infection rate; therefore, it can be surmised that the influence of trust in local government on the infection rate is realized through the impact of risk perception. In other words, risk perception mediates the relationship between trust in the local government and infection rate.

Some other interesting results are shown in Table 3. Surprisingly, at the city level, the population flow from Wuhan, which was demonstrated to have a strong influence in a previous study (Fan et al., 2020), showed no significant effect on the infection rate of COVID-19. This could be the different timing of the infection rate used in the study. Wuhan City was locked down on 23 January 2020, and the maximum incubation period of COVID-19 was 14 days. Therefore, the infection rate mainly caused by the population flow from Wuhan City can be estimated from January 23 to February 6th. Infection cases used in the previous study conducted by Fan et al. (2020) were studied for the period between January 25 and 31, They found that there is a high relationship between population flow from Wuhan and infection rate. However, because in this study, the infection rate considered was February 21, two weeks after February 6, and because the community infection within each city rather than the population flow became the main cause of the infection rate, the population flow from Wuhan was

Table 2
Correlations among dependent, independent and mediating variables.

	Infection rate	Risk perception	Generalized trust	Trust in central government	Trust in local government	Trust in central media	Trust in local media
Infection rate	1						
Risk perception	−0.240*	1					
Generalized trust	0.169*	−0.322*	1				
Trust in central government	−0.143*	0.101	−0.052	1			
Trust in local government	−0.275*	0.333*	−0.595*	0.284*	1		
Trust in central media	−0.195*	0.152*	−0.155*	0.949*	0.411*	1	
Trust in local media	−0.275*	0.355*	−0.559*	0.362*	0.846*	0.482*	1

N = 317, *$p < 0.05$, Intra-class Correlation is 0.285.

Table 3
Results of multilevel analyses regarding trust in government, cumulative infection rate on February 21, and risk perception.

	Model 1	Model 2
	Cumulative infection rate (logged) on February 21	Cumulative infection rate (logged) on February 21
Province level		
Trust in central government	−1.206 (0.931)	−0.795 (0.874)
Trust in local government	−1.817* (0.771)	−1.194 (0.739)
Risk perception		−1.480** (0.576)
Proportion of elderly people	8.502 (9.385)	9.657 (8.845)
Average education years	−0.331 (0.380)	−0.135 (0.368)
Unemployment rate	0.041 (0.416)	0.411 (0.379)
Average number of household persons	0.125 (0.813)	0.167 (0.728)
Proportion of social insurance expenditure	−0.593 (5.792)	−5.627 (5.494)
City level		
Population flow from Wuhan	1.997 (1.707)	1.930 (1.701)
Population density	9.041** (3.155)	9.703** (3.127)
GDP per capita	0.000* (0.000)	0.000* (0.000)
City type (Ref: prefecture-level cities)		
Central direct or province-capital cities	0.922** (0.332)	0.925** (0.330)
County-level cities	1.336*** (0.356)	1.296*** (0.353)
Hubei Province (Ref: other provinces)	3.455*** (0.982)	3.490*** (0.864)
Constant	9.103 (7.080)	7.212 (6.561)
Cities	317	317
Provinces	29	29
AIC	1235.428	1230.639
BIC	1288.053	1287.023

Standard errors are in parenthesis.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, †$p < 0.1$.

Table 4
Results of multilevel analyses regarding trust in media, cumulative infection rate on February 21 and risk perception.

	Model 3	Model4
	Cumulative infection rate (logged) on February 21	Cumulative infection rate (logged) on February 21
Province level		
Trust in central media	−0.319 (0.834)	−0.232 (0.776)
Trust in local media	−2.150* (0.855)	−1.492† (0.808)
Risk perception		−1.467** (0.553)
Proportion of elderly people	4.160 (9.450)	6.144 (8.934)
Average education years	−0.381 (0.367)	−0.174 (0.358)
Unemployment rate	0.210 (0.380)	0.488 (0.349)
Average number of household persons	−0.439 (0.802)	−0.221 (0.714)
Proportion of social insurance expenditure	−5.768 (5.387)	−8.609† (5.140)
City level		
Population flow from Wuhan	1.953 (1.713)	1.891 (1.704)
Population density	9.019** (3.148)	9.701** (3.116)
GDP per capita	0.000* (0.000)	0.000* (0.000)
City type (Ref: prefecture-level cities)		
Central direct or province-capital cities	0.909** (0.331)	0.916** (0.329)
County-level cities	1.296*** (0.355)	1.270*** (0.351)
Hubei Province (Ref: other provinces)	3.700*** (0.900)	3.624*** (0.810)
Constant	8.918 (6.675)	7.628 (6.217)
Cities	317	317
Provinces	29	29
AIC	1235.620	1230.046
BIC	1288.244	1286.430

Standard errors are in parenthesis.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, †$p < 0.1$.

deemed to have little or no effect on the infection rate of each city. Consistent with this reason, as shown in Table 4, the population density was positively and significantly associated with the infection rate, meaning that the population density in that city becomes an important factor in inducing the infection rate rather than the population flow from Wuhan. In addition, the GDP per person and the city type were crucial variables influencing the infection rate.

The third part estimates the relationship between trust in central and local media and the infection rate. The results are shown in Table 4.

Similarly, there are two models in Table 4. Model 3 included trust in central and trust in local media in the analyses. The results suggest that trust in central media was not significantly ($\beta = -0.319$, n.s.) associated with infection rate, while trust in local media was negatively and significantly ($\beta = -2.150$, $p < 0.05$) associated. This implies that trust in central media does not help reduce the infection rate, while trust in local media does. In Model 4, when risk perception is included, the effect of trust in local media becomes weaker (from −2.150 to −1.492), and the significance becomes greater (from less than 0.05 to less than 0.1). As shown in Table 4, trust in local media was positively and significantly associated with risk perception, meaning that it promotes coping behavior. In addition, in Model 4, risk perception was negatively and significantly associated with infection rate; thus, it can be said that the influence of trust in local media is partly through risk perception. In other words, risk perception partly mediates the relationship between trust in local media and the infection rate.

The final part estimates the effect of generalized trust on the infection rate; these results are shown in Table 5.

There are two models in Table 5. Model 5 shows the results without the mediating variable of coping behavior to health risk, while Model 6 shows the result with it. Because the regression coefficient of generalized trust was positive and significant ($\beta = 2.342$, $p < 0.1$) in Model 5, it means that generalized trust was positively associated with the infection rate. However, when risk perception was included in Model 6, the coefficient of generalized trust was non-significant ($\beta = 0.380$, n.s.), while risk perception was negatively and significantly ($\beta = -1.913$, $p < 0.01$) associated with the infection rate. These results have two implications: First, risk perception has a decreasing effect on the infection rate; that is, it can prevent people from being infected. Second, because in Table 5 it is confirmed that generalized trust reduces people's risk perception of health risk and that risk perception decreases the infection rate, the positive effect of generalized trust in Model 5 is through the influence of risk perception in Model 6, meaning that the relationship between generalized trust and infection rate is mediated by risk perception.

Regarding the robust check of these results which utilized the infection rate of COVID-19 on February 21, additional analyses using the infection rate of COVID-19 on March 15 and October 1 separately are conducted in Appendix 1 and 2. The two tables in the Appendix show that the regression consequences are totally consistent with the results of the infection rate on February 21. This indicates that there was no explosive growth of daily confirmed infections in any Chinese province

Table 5
Results of multilevel analyses regarding generalized trust, cumulative infection rate on February 21 and risk perception.

	Model 5	Model 6
	Cumulative infection rate (logged) on February 21	Cumulative infection rate (logged) on February 21
Province level		
Generalized trust	2.342†	0.380
	(1.344)	(1.312)
Risk perception		−1.913**
		(0.618)
Proportion of elderly people	2.361	12.387
	(12.974)	(11.864)
Average education years	−0.122	0.076
	(0.396)	(0.359)
Unemployment rate	0.455	0.720*
	(0.428)	(0.366)
Average number of household persons	−0.387	0.091
	(0.945)	(0.802)
Proportion of social insurance expenditure	−3.291	−9.610†
	(6.109)	(5.772)
City level		
Population flow from Wuhan	1.970	1.854
	(1.706)	(1.703)
Population density	9.418**	9.869**
	(3.161)	(3.120)
GDP per capita	0.000*	0.000*
	(0.000)	(0.000)
City type (Ref: prefecture-level cities)		
Central direct or province-capital cities	0.896**	0.911**
	(0.332)	(0.330)
County-level cities	1.270***	1.201***
	(0.354)	(0.350)
Hubei Province (Ref: other provinces)	3.983***	3.803***
	(1.051)	(0.864)
Constant	−10.855†	−2.593
	(6.265)	(6.268)
Cities	317	317
Provinces	29	29
AIC	1239.096	1232.618
BIC	1287.962	1285.243

Standard errors are in parenthesis.
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$.

except Hubei Province after February 21, and the results of the infection rate on February 21 are robust.

5. Discussion and conclusion

This study utilized an original dataset to estimate how the types of trust influenced the infection rate of COVID-19 in China. The analyses yielded three main results. First, the results suggested that trust in the local government helps decrease the infection rate, which is mediated by risk perception toward infectious diseases. It provided an empirical demonstration to prove that people who trust in the government will cooperate in coping with the infectious disease. Thus, the theory of heuristics is proved applicable in the study area of medicine. However, the results also found that trust in the central government had no effect on the infection rate. Since the correlation results showed that there is no significant relationship between trust in central government and risk perception, the central government has less influence on people's risk perception toward infectious diseases to reduce the infection rate.

Second, the results suggested that trust in the local media helps decrease the infection rate, with risk perception toward infectious diseases partly mediating this relationship. It demonstrated that, through the similarity heuristics and amplification theory, trust in the media improves people's risk perception toward infectious diseases and then reduces the infection rate. However, results also found that trust in the central media had no effect on the infection rate. Although, in the correlation analyses, the results showed that trust in central media had a significant influence on risk perception, while controlling for other variables, this relationship was decreased, having no effect on the infection rate. This result confirms that local media has a stronger influence on people than does central media.

Finally, the results indicated that generalized trust promotes a higher infection rate in that area. According to the analyses between generalized trust and risk perception toward infectious diseases, it was confirmed that generalized trust reduces people's risk perception toward the disease. This means that people who are more likely to unconditionally trust others are also more likely to have an optimistic attitude toward the risk of hazards. This is consistent with previous studies. The mediating analyses indicated that the positive effects of generalized trust on the infection rate are mediated by the risk perception of the infectious disease, meaning that the influence of generalized trust is through risk perception. Additionally, because the results of the relationship between generalized trust and trust in the government are negative, implying that generalized trust does not promote trust in government, the role of generalized trust in information flow from institutions to people seems invalid. This indicates that in the risk management of disease, generalized trust may not be the most appropriate type for coping with controlling the infection.

This study is related to the field of infectious diseases in several ways. First, it provides evidence to prove that the social aspect, especially trust, is a crucial factor in altering the infection of diseases. Current studies on infectious diseases mainly focus on factors such as population mobility and medical materials, while few studies pay attention to trust. However, without trust, people are unlikely to cooperate with governments taking preventive behaviors toward diseases, which could cause the infection rate of diseases to become uncontrolled. Therefore, for the risk management of diseases, it is crucial to not only improve objective medical conditions but also build trust in people. Accordingly, the government, especially the local government, should bear the responsibility of improving people's trust in it in daily life. For instance, because public service performance is the most essential area for citizens to judge whether the government should be trusted (e.g., Van de Walle and Bouckaert 2007), improving public service performance is an appropriate way to promote people's trust.

Second, it fulfills the theoretical and empirical gaps of how the types of trust influence the infection rate of the disease. Since there is no research on this topic, how types of trust impact the infection rate was unknown, and the mechanism of the impact was also ignored. This study quotes the theories of trust in the risk management of technologies to interpret its effect on the risk of diseases. Additionally, it utilized the dataset to demonstrate whether the theories applied are appropriate for this mechanism. Through these approaches, it provides a novel academic contribution to the study of the disease.

Finally, this study reveals the effects of different types of trust on the infection rate of the disease. Most previous studies on trust and risk perception only focused on one type of trust (Earle and Cvetkovich, 1995, 1997, 1999; Earle and Siegrist, 2008; Nakayachi and Cvetkovich, 2010; Siegrist et al., 2000, 2003). However, this could not capture the whole structure of the relationship between trust and disease. For instance, previous studies concerning vaccines suggested that generalized trust is related to trust in governments (Larson et al., 2018) and, accordingly, should have the same effect as trust in governments on the infection rate. If there is only a focus on trust in governments, and no focus on generalized trust, this speculation will still be deemed to be correct. This study provides empirical evidence to show that, in fact, the effect of trust in the government is different from generalized trust, suggesting that in the study of risk management on diseases, these two types of trust should be treated separately.

Although this study provides insights on the relationship between trust and infectious diseases, there are still several limitations that should be addressed by follow-up studies. First, this was a cross-sectional study rather than a dynamic one. The disadvantage of a cross-sectional study is the control of time-invariant variables. Exploring dynamic changes and the influence of trust on infectious diseases is a more complete and appropriate approach because it can estimate the real causal effect, except for time-invariant biases. Therefore, in future studies, it is necessary to consider a dynamic approach.

Second, the independent variables were collected from the CGSS2010, which was conducted 10 years ago. Although we provided theoretical evidence to prove that trust did not change so much in the last 10 years and, thus, assumed that the time gap did not have an effect on the influence of trust on the infection rate of COVID-19, we could not empirically provide this point. Therefore, in follow-up studies, a more recent dataset should be used to confirm the results of this study.

Appendix 1

Results of multilevel analyses of cumulative infection rate on March 15

	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
	Cumulative infection rate (logged) on March 15	Cumulative infection rate (logged) on March 15	Cumulative infection rate (logged) on March 15	Cumulative infection rate (logged) on March 15	Cumulative infection rate (logged) on March 15	Cumulative infection rate (logged) on March 15
Trust in central government	−1.059	−0.754				
	(0.748)	(0.683)				
Trust in local government	−1.360*	−0.813				
	(0.612)	(0.567)				
Trust in central media			−0.285	−0.200		
			(0.660)	(0.607)		
Trust in local media			−1.734*	−1.181†		
			(0.691)	(0.666)		
Generalized trust					1.949†	0.600
					(1.059)	(0.974)
Risk perception		−1.252**		−1.195**		−1.543**
		(0.459)		(0.446)		(0.493)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	6.258	5.190	6.283	5.672	−9.431*	−3.162
	(5.538)	(4.770)	(5.154)	(4.751)	(4.924)	(4.686)
Cities	317	317	317	317	317	317
Provinces	29	29	29	29	29	29
AIC	1040.345	1035.768	1039.812	1034.990	1043.972	1037.741
BIC	1092.970	1092.151	1092.437	1091.374	1092.838	1090.366

Standard errors are in parenthesis; Control variables are controlled in all models.
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$.

Appendix 2

Results of multilevel analyses of cumulative infection rate on October 1

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
	Cumulative infection rate (logged) on October 1	Cumulative infection rate (logged) on October 1	Cumulative infection rate (logged) on October 1	Cumulative infection rate (logged) on October 1	Cumulative infection rate (logged) on October 1	Cumulative infection rate (logged) on October 1
Trust in central government	−1.798	−1.153				
	(1.403)	(1.242)				
Trust in local government	−2.681*	−1.497				
	(1.169)	(1.074)				
Trust in central media			−0.685	−0.479		
			(1.261)	(1.094)		
Trust in local media			−2.817*	−1.639		
			(1.292)	(1.176)		
Generalized trust					3.361†	0.221
					(1.867)	(1.779)
Risk perception		−2.649**		−2.641**		−3.355***
		(0.877)		(0.841)		(0.948)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	23.535**	21.714**	21.887**	20.979**	−6.641	9.678
	(10.798)	(9.377)	(10.141)	(8.792)	(9.604)	(9.093)
Cities	317	317	317	317	317	317
Provinces	29	29	29	29	29	29
AIC	1561.240	1554.931	1562.540	1555.327	1564.835	1556.323
BIC	1613.864	1611.314	1615.165	1611.711	1613.701	1608.948

Standard errors are in parenthesis; Control variables are controlled in all models.
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2020.113517.

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