RIETI Discussion Paper Series 21-E-096

The Social Cognitive Determinants of Avoiding Crowded Places: Cultural Differences and Political Polarization

MATSUNAGA, Lucas Heiki
Tohoku University

AOKI, Toshiaki
Tohoku University

FAIAD, Cristiane
University of Brasilia

ALDRICH, Daniel
Northeastern University

TSENG, Po-Hsing
National Taiwan Ocean University

AIDA, Jun
Tokyo Medical and Dental University

RIETI
Research Institute of Economy, Trade & Industry, IAA

The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

RIETI Discussion Paper Series 21-E-096
December 2021

The Social Cognitive Determinants of Avoiding Crowded Places: Cultural Differences and Political Polarization*

Lucas Heiki Matsunaga[1], Toshiaki Aoki[1], Cristiane Faiad[2], Daniel Aldrich[3], Po-Hsing Tseng[4], Jun Aida[5]
[1] Tohoku University, Japan.
[2] University of Brasilia, Brazil.
[3] Northeastern University, The United States.
[4] National Taiwan Ocean University, Taiwan
[5] Tokyo Medical and Dental University, Japan.

Abstract

Why residents of large cities undertake physical distancing during pandemics remains understudied. This research seeks to explain this behavior through: (1) a structural model in a multinational sample, (2) differences in its components by culture, and (3) by political differences. A survey on planned behavior, risk perception, moral obligation, and political views was conducted with 1196 respondents in Taipei, Tokyo, New York, and Brasilia. Firstly, the structural model explained 47% of behavior in Brasilia, 36% in Tokyo, 33% in New York, and 20% in Taipei. Secondly, there were significant differences in the means of each component across cities with great effect, especially in fear of contagion, moral obligation, behavior, and trust in authorities, which may be sensitive to local norms and the public health situation. Finally, political polarization in each country meant deviation from the core model, especially in Brasilia, Tokyo, and New York, where contrasts between political partisans leads to different perceptions on the determinants of the model, with the largest difference found in trust in authorities and fear of contagion. Thus, reducing political polarization, understanding target segments of society, managing risk perception, feelings of moral obligation, and the social cognitive determinants of avoiding crowded places can be a strategy for communications based on scientific evidence.

Keywords: COVID-19; Social Psychology; Risk Perception; Avoid Crowded Places; Politics.

*This study is conducted as a part of the Project "Social Scientific Studies on Self-replicating Natural and Technical Phenomenon" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). Also, this study, in especial, involves the collaboration of a project conducted by members from Tohoku University, Tokyo Medical and Dental University (Japan), Northeastern University (The U.S.), University of Brasilia (Brazil), and the National Taiwan Ocean University (Taiwan) named “The Behavioral Mechanisms of cooperation during the COVID-19 pandemic: An international comparative analysis in Japan, The United States, Taiwan, and Brazil”. The author is grateful for financial support from Tohoku University and helpful comments and suggestions of Professor Masahiro Sato (Tohoku Uni.) and Professor Yuichi Furukawa (Aichi Uni), co-authors and Discussion Paper seminar participants at RIETI.

The Social Cognitive Determinants of Avoiding Crowded Places: Culture Differences and Political Polarization.

Living in big cities in the COVID-19 pandemic may be a challenge due to urban design, crowdedness, and extensive economic activities that influence people's opportunities to avoid crowded places. Nevertheless, few studies could propose an integrated model of explanation considering the political and social life of cities. Thus, we investigated the determinants of avoiding crowded places in four big cities in the world: Tokyo (Japan), Taipei (Taiwan), The City of New York (The U.S.), and Brasilia (Brazil). For that, we first verified the psychometric validity of a structural model based on the theory of planned behavior, risk perception, and moral norms. Then, we compared the mean scores of each component across cities, and finally by their political differences since COVID-19 can be highly politicized (Bartusevicius et al., 2021) and present significant different outcomes depending on national reactions (Cheng et al., 2020), where big cities may suffer higher from clusters of infection and consequences to all manners of human economy and activity (Kondo, 2020).

The background in Tokyo, Taipei, The City of New York, and Brasilia

During data collection, the daily increase and the cumulative number of deaths and cases related to the COVID-19 were higher in the Americas, but least in the Western Pacific countries[1]. Due to this contrast, we surveyed citizens from two big cities in the Americas and two in the Western Pacific: (1) Brasilia, (2) Tokyo, (3) Taipei, and (4) New York City, respectively, in Brazil, Japan, Taiwan, and the United States. We considered the cities to be (1) big centers, (2) having cultural and political differences, (3) having political and economic relevances for their respective countries, and finally (4) presenting differences in the COVID-19 background and public health measures. Thus, below, we briefly describe

[1] World Health Organization. WHO Coronavirus (COVID-19) Dashboard.

their urban, health, and political scenarios to understand the demands for citizens to avoid crowded places.

Brasilia, the capital of Brazil, is a planned city with a sectoral approach and large open spaces (Costa & Lee, 2019), making the city with a low population density of 3,094,325 people in 5,760 km² [2]. This city had in its federal district 300,393 cumulative cases of COVID 19 by March 3, 2021[3], when the country was under emergency state. Rising political polarization, conflicting information from the news and layers of government, and economic recession may be critical factors in the management of health policies (Lopes, 2021).

The City of New York constituted of 8,804,190 people living in around 783.83 km²[4], is one of the wealthiest and most crowded cities in the U.S. (Lankevich, 2020). The city had an emergency state[5] on March 3, an average of 3,972 new cases per week[6]. By the time, the conflict between Trump's administration and the World Health Organization, besides the already crescent political polarization (Pew Research Center, 2017), may have influenced adherence to COVID-19 measures (Kerr et al., 2021).

With 14,064,696 people living in 2,194 km², Tokyo maintained its Japanese regulatory law of non-compulsory measures, which is argued in previous studies to be significant in reducing human mobility (Yabe et al., 2020). Even though, in the Metropolitan area, it was observed 112,345 cumulative cases with COVID-19 by March 3, 2021[7]. The change of Prime Minister in the fall of 2020 left the country with years of political stability and positive evaluation, but yet with dilemmas with specific segments of society requesting a

[2] Brazilian Institute of Geography and Statistics, 2021.
[3] Public Security Secretary of the Federal District (2021).
[4] United States Census Bureau in 2019 for population and 2010 for the land area.
[5] New York State government (2021).
[6] The New York Times (2021).
[7] Tokyo Metropolitan Government (2021).

more steadiness position with health policies against COVID-19, which may conflict with the protection of business, economic sector and the Tokyo Olympics (Liff, 2021).

Taipei city yields a population density of 9,661 people per km² in 2020[8] , making it one of the densest urban areas in the world, besides the political and economic center of Taiwan (Britannica, 2019). Nevertheless, between February 28 to March 6, 2021, only 19 confirmed cases were found in the country, where rapid control of borders, travel restrictions, proactive testing, and other measures made it safer (Wang et al., 2020). In addition, data from the Taiwan National Security Survey showed stability in vote choice respecting a normal distribution, where for example, in Taipei City, politicians identified with moderates could have increased popularity among voters (Wang, 2019).

Theoretical Model

The theory of planned behavior.

To understand the efforts to engage in a behavior in a specific context and time, the theory of planned behavior (TPB) explains the need for: (1) attitudes, or the positive and negative evaluation of the behavior, (2) perceived behavioral control, or the easiness and controllability of performance, and (3) subjective norms or the social expectation for it (Ajzen, 1991). In a cross-cultural meta-analysis, Fischer & Karl (2021) showed the validity of the theory of planned behavior for understanding the many cooperative actions in the pandemic with 83 studies worldwide. For example, Schwander and collaborators (2021) found that the theory can predict social distance in the U.S. and Puerto Rico, while Mao and collaborators (2021) in China with avoiding nonessential conversation and personal contact. Other examples of studies involving protective behaviors against COVID-19 showed

[8] Department of Urban Development, Taipei City Government (2021).

evidence in the Philippines, Iran, Norway, Israel, or Bangladesh (see Das et al., 2021, Lin et al., 2020, Prasetyo et al. 2020; Wolff, 2021; Fan et al., 2021; Shmueli, 2021). Nevertheless, studies on avoiding crowded areas, including additional components of risk and feelings of moral obligation, are needed to cover part of the variance of behavior not explained by the theory of planned behavior, since noncooperation may put the self at risk and may affect others due to COVID-19 being a highly infectious disease.

Risk Perception

International evidence showed that risk perception significantly correlates with preventive health behaviors against COVID-19 (Dryhurst et al., 2020). But, although people make deliberative evaluations about their risks, such as estimating the likelihoods in decisions on a utility basis, behavioral economics showed that people are also guided by loss aversion and heuristics (Kahneman & Tversky, 1979); or emotions such as fear and affect (Slovic et al., 2007). For example, a meta-analysis over 136 effect sizes in various studies verified that fear has a significant and average effect of r=.219 on decreasing risk-taking. Furthermore, Frounfelker and collaborators (2021), with an expanded model of the theory of planned behavior, found in Canada (N= 3,183) that fear of infection can be a significant predictor for more efforts in practicing social distance (β = .16; S.E. = .01, $p<.001$).

In addition, the frequency of exposition to related information and the social trust in the authorities' policies may influence intuitions about risks and fear (Tversky & Kahneman, 1973; Cvetkovich, 2013; Ng & Kemp, 2020). Thus, to measure risk perception, we considered (1) cognitive risk evaluation (the likelihood and magnitude estimation of contagion), (2) social trust (evaluation of health policies against COVID-19 by national authorities), and (3) frequency of exposed information about COVID-19 (In the news, social

media, and face-to-face communication) as predictors of fear of contagion leading to effects on behavior.[9]

Feelings of Moral Obligation

Avoiding crowded places is necessary for the collective benefit of controlling clusters of infection in cities, but it can present a social dilemma if it produces individual costs. Thus, consequences generated by adopting this behavior, such as depriving citizens of places they want to go, participating less in economic life, or creating burdens in planning new routes, can encourage defection. However, even though against one's utility, there is much evidence from cross-cultural experiments for a cooperative tendency in human decision-making (Henrich et al., 2005). This tendency can be a product of cultural foundations (Haidt, 2012), genetic relations (Foster et al., 2006), evolutionary heritage (De Waal, 2008), or ontological and emotional development (Kohlberg & Hersh, 1977). But in general, the awareness of others' needs, such as vulnerable people, may provoke emotional arousal and feelings of obligations (Schwartz, 1977), influencing cooperation. This experience of empathy can be the need for care over populations at higher risk against COVID-19, such as people over 60 years old or with lung or heart disease, diabetes, and other health conditions (World Health Organization, 2021). And indeed, international research showed that emotions such as empathy for people vulnerable to the virus could be seen as an essential component of

[9] All components, separately, have significant correlation with avoiding crowded places in our sample. Fear predicted in r=.327 (p<001), trust in r=-.214 (p<.001), frequency of COVID-19 information in r=.152 (p<.001), and cognitive risk evaluation in r=.184, (p<.001). With multiple regression, only trust (r= -.137, p< .001) and fear (r=.283, p<.001) would be significant predictors of behavior. Considering their effects, it is possible to see that fear is the one closer in explained variance to the behavior. Thus, taking the literature on the affect heuristic, we opt to explain the behavioral decision as influenced by their currrent emotions mainly, and indirect influenced by the other variables, which all are significant predictors of fear (p< .001). This was considered due to the nature of the behavior, that although may require planned action, it is also constrained by habits or constrained demands that evoke heuristics or mental shortcuts based on emotions, influencing directly the behavior.

adhering to physical distancing (Pfattheicher et al., 2020). Thus, we included feelings of moral obligation to explain efforts and behavior.

An integrative model

The theory of planned behavior can explain health behaviors but still lacks explained variance when they involve risks (McEachan et al., 2011) and moral norms if they present social dilemmas (Parker et al., 1995; Chan & Bishop, 2013). This is because the theory doesn't include these components in its model, needing an expanded version. Thus, we propose a model where the behavior would be influenced directly by intention, moral norms, and fear. Then, risk evaluation, frequency of COVID-19 information, and trust in health policies from own government were assigned to impact fear. At the same time, intentions would be influenced by attitudes, perceived behavioral control, injunctive norms (social expectations), and moral norms (see Figure 1). Then, we considered cross-cultural differences in the model's estimates and analyzed all these components` mean scores by culture and political views. By doing that, it would be possible to verify how communications and psychological interventions can be designed while preserving citizens' freedom, well-being, and safety.

Method

Data collection and questionnaire

This research, approved by the research ethics committee (IRB number 2020-2), used a Likert type scale of five points for measuring (1) attitudes, (2) injunctive norms, (3) moral norms, (4) trust in authorities, (5) perceived behavioral control, (6) risk evaluation of contagion, (7) fear of infection, (8) frequency of exposition to COVID-19 information, and (9) intentions. In addition, another question with 7 points for measuring the number of times that people avoid crowded places when going out. The survey was conducted online between

December 31, 2020, to March 3, 2021, where private survey companies (Qualtrics and Cross-Market) collected data in New York City, Japan, and Taiwan using criteria for the sample to be above 18 years old, having equal distribution of gender and an equal number of participants for each age groups broken in 10 (From 20 years old to over 65). In Brasilia, the researchers conducted snowball sampling due to national regulations. The questionnaire, initially written in English, was translated to Portuguese, Mandarin Chinese, and Japanese. Then, it was back-translated, and the items were compared in both versions for quality and preservation of the original meaning of each question. All translators were native in their respective languages and had an academic background. Each item, mean score, standard deviation, and Cronbach's alpha for their dimensions can be seen in Table 1.

Table 1

Means (M) and Standard Deviations (S.D.) of each item, followed by their reliability score (Cronbach's alpha) in their respective dimension.

Items	***M***	***SD***	**α**
Attitude			
Avoiding crowded places is good for me.	4.33	.8	
Avoiding crowded places is desirable.	4.26	.84	.795
Injunctive Norm			
People tell me to avoid crowded places.	4.25	.8	
It is expected of me to avoid crowded places.	4.23	.85	.703
Perceived Behavioral Control			
I am confident that I can avoid crowded places.	3.96	.95	
It is easy for me to avoid crowded places.	3.8	1.01	.81
Moral Norm			
I would feel guilty if I stay in crowded places.	3.64	1.09	
I believe that I have a moral obligation to avoid crowded places.	3.92	1.0	
Staying in crowded places goes against my moral principles.	3.62	1.1	.853
Intention			
I intended to avoid crowded places.	4.21	.9	
I made an effort to avoid crowded places.	4.25	.84	.787
Behavior			
In the midst of the coronavirus pandemic, how often do you stay at home, weekly, due to this pandemic, except to buy daily necessities?	5.23	1.51	Not applicable
Cognitive Risk Evaluation			
About being affected by catching the coronavirus in the near future. I think I will be directly affected by it.	3.39	1.04	
About being affected by catching the coronavirus in the near future. I think I will seriously be affected by it.	3.24	1.02	.849
Frequency of COVID-19 Information			
Frequency of COVID-19 information on the T.V., radio, and newspapers.	4.22	1.01	
Frequency of COVID-19 information on social media.	3.85	1.22	
Frequency of COVID-19 information in face-to-face communication.	3.64	1.14	.69
Trust in Authorities			
The national government can generally be trusted to manage the COVID-19 crisis OR In 2020, I thought the federal government could be trusted to manage the COVID-19 crisis(THE US).	2.81	1.29	
The COVID19 policies of my country should be changed.	2.41	1.1	
COVID-19 policies in my country are effective in protecting people's basic health.	2.93	1.21	.769
Fear			
Getting sick with the coronavirus can be a worry.	3.86	1.03	Not applicable

Sample characteristics

The sample consisted of 1196 participants (including 300 in Taipei, 300 in Tokyo, 313 in the City of New York, and 283 in Brasilia), 58.9% women with a mean age of 44 years old (*SD*= 14). This sample doesn't contain invalid questionnaires or outliers since they were substituted to others before data analysis. Unemployed people were 16.7%, while 35.9% worked remotely, and only 30 participants declared staying under quarantine. Most participants declared being centrists in their political view (42%), and people not interested in politics were verified to be substantial (20.2%), but each country considers the political spectrum in different terms. From one opposition to another, in Brazil, we considered the division in Left-wing and Right-wing, in the City of New York Republicans and Liberals, in Taipei Democratic Progressive Party (DPP) and the Kuomintang (KMT)/ the Chinese Nationalist Party, and finally in Tokyo Progressists and Conservatives. Socio demographics can be visualized in Table 2.

Table 2

Socio-demographics of all cities or by cities

Baseline Characteristics	All Cities (N=1196)		The City of New York (N= 313)		Tokyo (N=300)		Taipei (N=300)		Brasília (N=283)	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Gender										
Female	701	58.6	196	62.6	151	50.3	150	50	204	72.1
Male	492	41.1	117	37.4	149	49.7	150	50	76	26.9
Political Position										
Left-Wing/Liberals/ Progressives/DPP	264	22.1	96	30.7	40	13.3	50	16.7	78	27.6
Right-Wing/Conservatives/ Republicans/ KMT	184	15.4	56	17.9	46	15.3	38	12.7	44	15.5
Centrist	502	42	102	32.59	163	54.3	166	55.3	71	25.1
Not Interested	242	20.2	59	18.84	51	17	46	15.3	86	30.4
Highest education										
Other	80	6.7	8	2.6	3	1	62	20.6	7	2.5
High school	201	16.8	74	23.6	33	11	52	17.3	45	14.8
Undergraduate degree	658	55	126	40.3	195	65	166	55.3	171	60.4
Masters degree	209	17.5	85	27.2	64	21.3	13	4.3	47	16.6
Ph.D.	48	4	20	6.4	5	1.7	7	2.3	16	2.7
Working remotely										

Yes	429	35.9	131	41.9	75	25	75	25	148	52.3
No	565	47.2	119	38	145	48.3	188	62.7	113	39.9
Unemployed	200	16.7	63	20.1	80	26.7	37	12.3	20	7.1
Cases under 1uarantine	30	2.5	19	6.1	2	0.7	2	0.7	7	2.5
Cases that contracted coronavirus	79	6.6	32	10.2	1	0.3	1	0.3	45	15.9

Note. For all countries N = 1196, for the City of New York N = 313, for Tokyo N = 300, for Taipei N = 300, and for Brasilia N = 283 . Participants were on average 44.10 years old (SD = 14.844).

Results

Data Analysis

The results were described and discussed in three sections: (1) overall model and multigroup analysis, (2) comparison of the mean scores between cities, and (3) comparison of the scores by political positions for each country. Thus, for the first section, we aimed to verify the validity of the structure in the overall model involving all the samples by applying Structural Equation Modeling (SEM) using AMOS SPSS v.26 with estimates based on Maximum Likelihood, following minimum (Bentler, 1992; Byrne, 2013) or superior criteria (Hu & Bentler, 1999) respectively: χ^2 with $p \leq .05$, Root Mean Square Error of Approximation (*RMSEA*) ≤ 0.08 or ≤ 0.05, Comparative Fit Index (*CFI*) ≥ .90 or.≥ 95, *NFI* ≥ .90 or ≥ .95, and Tucker-Lewis Index (*TLI*) ≥ .90 or ≥ .95. Later, because this research works with a sample from four different countries, we conducted a multigroup analysis to verify which estimates can be assumed to be equal across cities.

For the second section, we verified with ANOVA the differences between the mean scores of the countries. Then, in the third section, we compared the mean scores between political positions in each country. For this, we used Welch's ANOVA (Robust Test of Equality of Means), which can have better control over violations in the homogeneity of variance or differences in the number of participants across groups (Delacre et al., 2019). Welch's ANOVA was conducted because data collection did not establish criteria for selecting the number of participants equal for each political category. It was expected that

most of the population would tend to identify with their countries` center. This data collection confirmed this last assumption. Finally, in sections 2 and 3, Bonferroni post hoc detail the most significant differences. Also, Bayes Factor, conducted in JASP v.0.14.1.0, showed how much the effects are more likable under the alternative (M1) than the null model (M0) (Ly et al., 2016). Compared to *p*-values, this last would show higher reliability of significances and is significantly more informative in large samples (Marden, 2000).

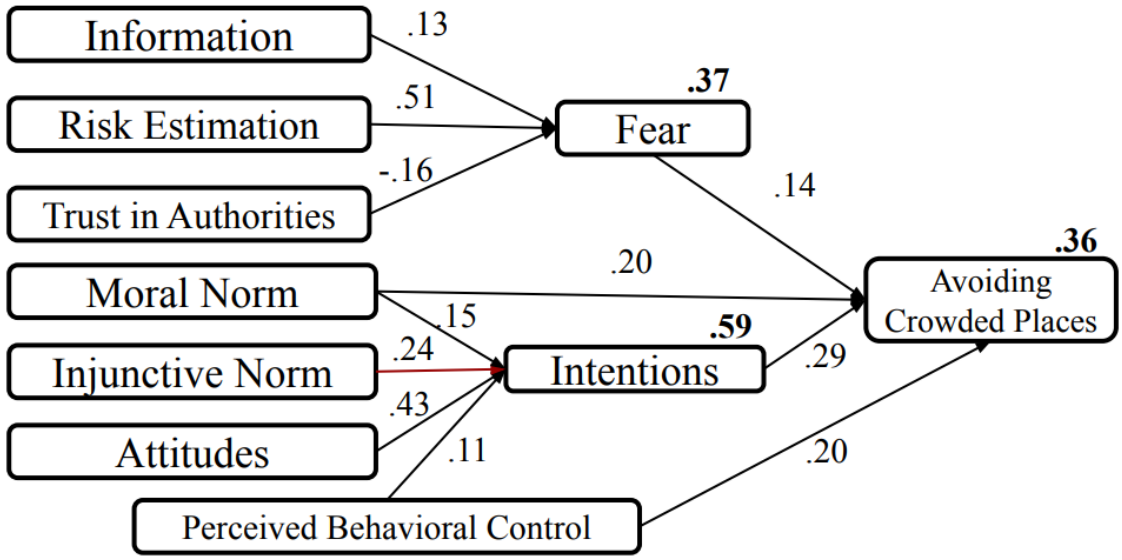
Section 1: Overall model and Multi-Group Analysis

Results

It was verified that the entire data fits the model well with $\chi^2 = 123.124$ ($p < .00$), CFI = .974, NFI= .97, TLI= .921 and RMSEA= .078, 95% CI [.065 to .091] (see Table 3). Thus, it was possible to explain around 37% of the variance in fear of contagion, 59% in intention, and 36% in behavior (see Table 4). In summary, to explain the structure of the model (see Figure 1), fear of infection is influenced positively by frequency of information related to COVID-19 (β=.13, $p < .001$) and negatively by trust in authorities and health policies (β=-.16, $p < .001$), but mostly positively by the risk estimation (β=.51, $p < .001$). Intention is influenced positively by moral norm (β=.15, $p < .001$), injunctive norm (β=.24, $p < .001$), perceived behavioral control (β=.11, $p < .001$) and attitude (β=.43, $p < .001$). Then, the reported behavior of avoiding crowded places can be analyzed by the influence of fear (β=.14, $p < .001$), moral norm (β=.20, $p < .001$), intention (β=.29, $p < .001$), and perceived behavioral control (β=.20, $p < .001$).

Figure 1

The overall model with its standardized estimates and total effects (in bold).



For multigroup analysis, a model considering all cities as different groups was analyzed with all parameters to be freely estimated (Unconstrained), showing good fit: χ^2= 168.696 (p < .001), CFI = .972, NFI= .959, TLI= .917 and RMSEA= .039, 95%CI [.032 to .046]. Then, to compare with a constrained model where all estimates are forced to be equal across the cities, we verified significant, but worst fit (CMIN difference of 90.212, p<.001): χ^2= 258.908 (p < .001), CFI = .958, NFI= .937, TLI= .918 and RMSEA= .039, 95%CI [.033 to .044]. Because of that, a step by step analysis of each estimate revealed the ones that could be constrained without significantly harming the fit (p>.05): PBC (CMIN= 5.708, p=.127), moral norm (CMIN= 4.268, p=.234), and attitude (CMIN= 6.908, p=.075) to intention; frequency of COVID-19 information (CMIN= 3.237, p=.357), and trust in authorities (CMIN= 2.233, p=.526) to fear of infection; and fear (CMIN= 2.835, p=.418), and moral norm (CMIN= 1.055, p=.788) to behavior. Finally, when these parameters were constrained, letting others to be freely estimated in order to propose a partially constrained model, we could achieve significant better fit χ^2= 196.378 (p < .001), CFI = .971, NFI= .959, TLI= .935 and RMSEA= .035, 95%CI [.028 to .041] (see Table 3 for all fit scores). With this last, it was possible to explain 47% of behavioral variance in Brasilia, 36% in Tokyo, 33% in the City of New York and 20% in Taipei. Explanation in efforts were observed to be greater

in Tokyo (69%), while fear was explained better in Taipei (38%) (see Table 4).

Table 3

Results for Fit Measures of the Models.

	Overall	Unconstrained	Constrained	Partially constrained	Reference Scores
$\chi^2(p)$	123.124 (p < .001)	168.696 (p <.001)	258.908 (p <.001)	196.378 (p <.001)	p <.05
df	15	60	93	81	
CFI	.974	.972	.958	.971	≥ 0.90 or 0.95
NFI	.970	.959	.937	.959	≥ 0.90 or 0.95
TLI	.921	.917	.918	.935	≥ 0.90 or 0.95
RMSEA: [90% CI]	.078 [.065 to .091]	.039 [.032 to .046]	.039 [.033 to .044]	.035 [.028 to .041]	≤ 0.08 or ≤ 0.05 90% CI

Note. χ^2 = chi-squared*; df* = Degree of Freedom*; CFI* = Comparative Fit Index*; TLI* = Tucker–Lewis Index*; RMSEA = Root Mean Square Error of Approximation Index; CI* = Confidence Interval. Minimum reference scores based on Bentler (1992) and Byrne (2013), and superior based on Hu & Bentler, (1999) and Byrne (2013) again.

Table 4

They squared Multiple Correlations of fear, intention, and behavior in the overall and multigroup models where only significant equal regression weights are constrained.

		Model per city (Partially constrained)			
Variables	*Overall Model*	*Tokyo*	*Brasilia*	*The City of New York*	*Taipei*
	R^2	R^2	R^2	R^2	R^2
Fear	.373	.364	.321	.273	.376
Intention	.591	.691	.512	.598	.477
Behavior	.358	.355	.467	.328	.195

As for the estimates, moral norm (β=.268, $p < .045$) and fear of infection (β=.158, $p < .001$) were constrained to predict behavior, but the effect of intention varied across the cities while being a better predictor in the City of New York (β=.714, $p < .001$), Tokyo (β=.621, $p < .001$), and Brasilia (β=.592, $p < .001$), respectively (see Table 5). Thus, if the independent variables of intention are changed for these countries, we could expect a great indirect impact on the actual behavior. Intention can be predicted equally across the cities by

PBC (β=.09, $p < .001$), moral norm (β=.114, $p < .001$) and attitudes (β=.472, $p < .001$), but differently by the injunctive norm, which presented better effects in the City of New York (β=.335, $p < .001$) and Tokyo (β=.329, $p < .001$). Then, fear can be predicted equally by frequency of COVID-19 information (β=.136, $p < .001$) and trust in COVID-19 health policies (β=-.146, $p < .001$), but not by risk estimation that was a better predictor in Tokyo (β=.662, $p < .001$) and Taipei (β=.599, $p < .001$).

Table 5

Standardized estimate, Standard Errors, and significance of the estimates in the partially constrained model.

Estimates		The City of New York (N=313)			Tokyo (N=300)			Brasília (N=283)			Taipei (N=300)		
Dependent	Independent	*β*	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*	*β*	*SE*	*p*
Intention	Injunctive Norm	.335	.044	***	.329	.042	***	.177	.047	***	.164	.045	***
Intention	PBC	**.09**	**.019**	***	**.09**	**.019**	***	**.09**	**.019**	***	**.09**	**.019**	***
Intention	Moral Norm	**.114**	**.02**	***	**.114**	**.02**	***	**.114**	**.02**	***	**.114**	**.02**	***
Intention	Attitude	**.472**	**.028**	***	**.472**	**.028**	***	**.472**	**.028**	***	**.472**	**.028**	***
Fear	Risk Evaluation	.474	.05	***	.662	.054	***	.381	.043	***	.599	.05	***
Fear	Information	**.136**	**.028**	***	**.136**	**.028**	***	**.136**	**.028**	***	**.136**	**.028**	***
Fear	Trust	**-.146**	**.027**	***	**-.146**	**.027**	***	**-.146**	**.027**	***	**-.146**	**.027**	***
Behavior	PBC	.133	.091	.145	.300	.085	***	.47	.071	***	.533	.106	***
Behavior	Intention	.714	.095	***	.621	.094	***	.592	.1	***	.124	.111	.264
Behavior	Fear	**.158**	**.035**	***	**.158**	**.035**	***	**.158**	**.035**	***	**.158**	**.035**	***
Behavior	Moral Norm	**.268**	**.045**	***	**.268**	**.045**	***	**.268**	**.045**	***	**.268**	**.045**	***

Note. ***p < .001. Scores in bold are constrained (equal) across the cities

D*iscussion*

We could achieve a good fit with the overall model but better when conducting multigroup analysis, showing the need to compare each estimate by culture to find differences and similarities. By doing so, the model explanation of our research finding produced substantial explained variance compared to previous literature on the planned behavior theory related to health behaviors, especially involving risks (McEachan et al., 2011). However, when looking at the partially constrained model, it showed less behavioral

explanation in Taipei. This result could be due to the controlled situation of COVID-19 cases and fewer burdens associated with preventive measures, which presents less need for planned action or less arousal of emotions for behavioral change.

In particular, the explanation of fear in both Taipei and Tokyo was higher than in other cities, even though facing a better public health scenario. This explanation may be due to the lower effect of risk estimation on fear in the City of New York and Brasilia, leading to whether the constant crisis in these last cities desensitized citizens in the long run as a coping mechanism. A study in Brazil conducted by Barros et al. (2021) showed that pregnant health workers had a habituation process to cope with the constant fear of COVID-19 infection, diminishing the effect of risk estimation on anxiety and fear. In the next section, one can verify that the mean score of fear in Brazil and the City of New York was the highest, making it difficult for increasing even more.

Also, Moral norms, differently from injunctive norms, presented similar effects on behavior and intention across countries. This difference can be a piece of potential evidence that personal norms can be genuinely an independent construct of social norms. The first is centered on the self and the individual's experience of empathy, and the other is a cue on how people should act (Schwartz, 1977). Thus, the experience of empathy may be a human condition without so many variations across cultures, while codes of conduct created by societies can vary broadly, mainly due to the sensitivity of some cultures to the need of controlling uncertain events (Hofstede, 2011).

Section 2: Comparison of the mean scores between cities.

Results

It was verified a significant difference in all measures across countries with ANOVA (p<.001) (see Table 6). Brasilia scored higher in most of the measures, except for trust in health policies, where it scored lowest (M= 1.91, SD=1.01), while Taipei the highest (M=

3.37, *SD*= .73). Tokyo presented the lowest scores among all cities in PBC (*M*=3.46, *SD*=.91) and moral norms (*M*=3.38, *SD*=.90). The city also presented low scores similar to Taipei in intention (*M*=4.03, *SD*=.821) and fear (*M*=3.59, *SD*=1.01), which Taipei scored the lowest for the last (*M*=3.55, *SD*=1.05). In behavior, people in Taipei report avoiding crowded areas the less (*M*=4.67, *SD*=1.33), followed by Tokyo (*M*=4.85, *SD*=1.50), then New York City (*M*=5.57, *SD*=1.503) and Brasilia (*M*=5.86, *SD*=1.35), respectively. For this measure, comparison between groups showed a significant effect size (*F*=46.63, *p*<.001, *η2*=.105) compared to other estimates, except for trust (*F*=161.20, *p*<.001, *η2*= .289). Bayes factor also suggests strong evidence for all differences (BF10>10 for strong evidence) with low fluctuation (the error is less than 10%).

Table 6

Mean and Standard Deviation of scores by country, followed by results from ANOVA and Bayes Factor.

	Tokyo (N=300)		Taipei (N=300)		The City of New York (N=313)		Brasília (N=283)		*F*	*η2*	*BF10*	*error%*
Measure	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*				
Fear	3.59	1.01	3.55	1.05	3.97	.97	4.37	.85	45.10***	.102	2.42e+27	.002
Intention	4.03	.821	4.05	.707	4.34	.81	4.51	.71	26.99***	.064	6.328e+13	.0044
Behavior	4.85	1.50	4.67	1.33	5.57	1.5	5.86	1.35	46.63***	.105	1.855e+25	.002
COVID-19 Information	3.78	.88	3.88	.91	3.67	.90	4.32	.69	32.53***	.076	1.19e+20	.017
Risk Estimation	3.13	.88	3.12	.98	3.46	.93	3.55	.99	16.72***	.04	4.30e+07	.045
Attitude	4.21	.77	4.16	.69	4.21	.80	4.63	.61	26.13***	.062	1.918e+13	.045
Moral Norm	3.38	.90	3.54	.80	3.84	.92	4.18	.91	47.12***	.106	3.455e+25	.003
Injunctive Norm	4.26	.74	4.03	.71	4.23	.73	4.45	.65	16.38***	.040	2.648e+7	.051
Social Trust	2.57	.83	3.37	.73	2.98	.77	1.91	1.01	161.2***	.289	9.971e+83	2.51e-4
PBC	3.46	.91	3.91	.74	4.03	.85	4.15	.93	36.61***	.084	2.987e+19	.005

***p < .001. *Error%* denotes how much fluctuation exists in the results. *BF10* stands for Bayes Factor compared to a null model.

Discussion

With these results, we could find differences in all mean scores across the cities, showing that cultural matters also explain the variance of all components. Firstly,

assumptions involving the low performance of avoiding crowded places in Taipei must consider the low score of its predictors and the controlled situation of the country over the pandemic. Therefore, trust in this country may be higher than the other countries due to this last consideration. Nevertheless, in general, the most considerable difference found in trust in health policies may be due to the differences in countries` scenarios and how effectively the policies may have been to reduce the pandemic.

Secondly, Tokyo did not show perceived behavioral control as high as other countries, even though being a relatively good estimate for behavioral change by looking at the model in section 1. Thus, mechanisms such as better environmental design or explicit instructions to improve this measure can play a role in nudging this behavior. Also, even though injunctive norms scored high in Tokyo, the same does not apply to moral norms. Thus, policies should distinguish whether they target people's feelings of moral obligation or influence them through social expectations.

Finally, Brasilia and the City of New York scored high for almost all the components, being in congruency both to the explained variance in the previous model and to their COVID-19 situation by the time of data collection, where for example, cognitive risk evaluation and fear seems to be a significant product of their public health situation. For being in close contact with a public health crisis, people in these cities would evaluate how this behavior is essential while also producing more efforts and actual behavior for self-prevention. In addition, high feelings of moral obligation and fear may also be a product of close contact with the reality of deaths and social consequences such as the congestion of beds, people under vulnerable conditions, and the need for protecting nearby friends, their families, and themselves.

Analysis 3: Comparison of the scores by political position in each country

Results

Firstly, Taipei showed no differences in the measures across the political dimensions, except for moral norms (F=3.308, p<0.05, η2= .036) and trust in authorities (F=5.240, p <0.01, η2= .047). For moral norms, the most remarkable difference was between centrists (M=3.663, SD= .78) and citizens not interested in politics (M=3.261, SD=.883) with a significant and medium effect of Cohen's d=.502. For trust in authorities, the most remarkable difference was between partisans with DPP (M=3.68, SD= .646) against KMT (M=3.149, SD=.812), or not interested (M=.3.232, SD=.720). These last differences showed significantly ($pbonf$<.001) and medium to a high effect size of Cohen's d= .735 and .657, respectively.

In Japan, otherwise, political differences showed to be significant in 6 measures, with the most effect size on intention (F=6.865, p <0.01, η2= .057) and trust (F=7.891, p <0.01, η2= .084). No significant difference was found in behavior, but people not interested in politics put significant fewer efforts into practicing this behavior (M= 3.716, SD= .716) than partisans such as Conservatives (M= 3.848, SD= .971), Progressists (M= 4.360, SD=.709), and Centrists (M=4.101, SD=.8). These efforts would vary because of indirect factors such as positive attitudes (F= 4.184, p <0.05, η2= .031), social pressure (F=5.248, p <0.01, η2=.051), and feelings of moral obligation (F=3.614, p <0.05, η2= .034). Conservatives, although scoring high in injunctive norms (M=4.022, SD=.856), still present significantly less ($pbonf$<.05) with upper medium effect size (Cohen's d=.646) compared to Progressists (M=4.5, SD=.702). With trust in the health policies, these differences seem to be even high between the same groups, with Conservatives presenting more trust (M= 3.01, SD= .90) than progressists (M=.26, SD=.94), with high effect size (Cohens's d= .813, p<.001). The differences between Conservatives and Centrists are also high with Cohen's d= .7 ($pbonf$<.001).

Table 7

Results of Welch's ANOVA (Robust Test of Equality of Means) and Bayes Factor of the differences between the four political interests in Tokyo and Taipei.

	Tokyo				Taipei			
Measure	*F*	*η2*	*BF10*	*error%*	*F*	*η2*	*BF10*	*error%*
Fear	3.825**	.038	3.32	7.041e-4	1.701	.017	.164	6.847e-4
Intention	6.865***	.057	30.020	.011	.158	.002	.026	.011
Behavior	1.446	.013	.1	.002	.39	.004	.034	.009
Information	2.553	.031	1.018	2.062e4	.217	.002	.027	.011
Risk Evaluation	.869	.009	.064	.004	1.072	.010	.071	.003
Attitude	4.184*	.031	.878	1.515e-4	.986	.013	.106	.002
Moral Norm	3.614*	.034	1.398	1.984e-4	3.308*	.036	2.551	6.228e-4
Injunctive Norm	5.248**	.051	14.562	.031	.163	.002	.025	.012
Trust in Authorities	7.891***	.084	1561.785	.001	5.240**	.047	8.291	.033
PBC	.212	.002	.027	.011	1.311	.012	.093	.002

Note. ***p < .001; **p < .01; * p<.05; Others are not significant (p>.05). *Error%* denotes how much fluctuation exist in the results. *BF10* stands for Bayes Factor compared to a null model.

The political differences in the City of New York presented to be significant in fear (*F*=6.388, *p* <0.001, η2=.054), intention (*F*=4.273, *p* <0.01, η2=.045), behavior (*F*=3.879, *p* <0.05, η2=.036), frequency of information (*F*=3.593, *p* <0.05, η2=.037), attitude (*F*=4.572, *p* <0.01, η2=.037) and trust in authorities (*F*=5.658, *p* <0.001, η2=.051), with small to medium effect size. In behavior, the big difference was found between Liberals (*M*= 5.938, *SD*=1.312) against Republicans (*M*=5.232, *SD*=1.629), or citizens not interested in politics (*M*=5.254, *SD*=1.636) with Cohen's *d*= .491(*pbonf*=.03) and .473 (*p*=.034) respectively. In intention the big difference was between Liberals (*M*= 4.536, *SD*=.749) against Republicans (*M*=4.080, *SD*=1.008) with Cohen's *d*= .541 (*pbonf* <.004), while fear also presented bigger differences between Liberals (*M*= 4.281, *SD*=.804) against Republicans (*M*=3.661, *SD*=1.049) with Cohen`s *d*= .688 (*pbonf* <.001). Finally, following the same tendency, trust was higher with Republicans (*M*= 3.292, *SD*=.691) than Liberals (*M*=2.785, *SD*=.828) with Cohens *d*= .650 (*pbonf*<.001).

Brasilia showed the greatest differences in the scores by political positions, being all of them, but PBC, significant (see table 8). The most evident difference is trust in authorities

with high effect size (F=42.87, p<.001, $\eta 2$=.261), where Right-wing (M=2.902, SD= .882) trust highly more than Left-Wing (M=1.286, SD=.590), and centrist (M= 1.845, SD= .949), with Cohen`s d = 2.279 and 1.143, respectively ($pbonf$ <.001). Fear presented the second greatest difference (F=12.49, p<.001, $\eta 2$=.163), followed by moral norm (F=12.34, p<.001, $\eta 2$=.151) and both intention (F=5.81, p<.001, $\eta 2$=.1) and behavior (F=5.67, p<.001, $\eta 2$=.1). For these measures, Right-wing partisans reported fewer feelings of moral obligation (M=3.432, SD=1.211) with significant and high differences from Left-wing (M=4.536, SD=.577) (Cohen`s $d$= 1.285, $pbonf$<.001), centrist ($M$=4.265, $SD$=.866) (Cohen`s d= .824, $phone$ <.001) and not interested (M=4.182, SD=.814) (Cohen`s d= .777, $pbonf$<.001). Right-wing also fearless (M=3.636, SD=1.313), had less intention (M=4.011, SD=.985) or reported less behavior of avoiding crowded places (M=4.886, SD=.1.858), with significant (p<.001) and medium to high effect size in score differences (Cohen's d varying from .679 to 1.218) from any other groups in these measures.

Table 8

Results of Welch's ANOVA(Robust Test of Equality of Means) and Bayes Factor of the differences between the four political interests in the City of New York and Brasilia.

	The NYC				Brasilia			
Measure	*F*	*η2*	*BF10*	*error%*	*F*	*η2*	*BF10*	*error%*
Fear	6.388***	.054	29.101	4.545e4	12.489***	.163	5.468e+7	3.855e-4
Intention	4.273**	.045	7.312	5.520e-4	5.810***	.100	4732.962	.013
Behavior	3.879*	.036	2.19	5.893e-4	5.670***	.100	4839.071	.017
Information	3.593*	.037	2.327	5.362e-4	4.360**	.045	3.903	4.676e-4
Risk Evaluation	1.318	.014	.097	.002	5.535***	.067	67.883	.005
Attitude	4.572**	.037	2.655	6.034e-4	6.806***	.091	1612.823	.001
Moral Norm	1.786	.016	.135	.001	12.340***	.151	8.154e+6	.003
Injunctive Norm	1.806	.020	.233	2.833e-4	3.239***	.044	2.984	3.223e-4
Trust in Authorities	5.658***	.051	17.340	3.929e-4	42.869***	.261	6.623e+14	1.738e-4
PBC	2.176	.019	.176	5.887e-4	2.656	.036	1.116	2.427e-4

Note. ***p < .001; **p < .01; * p<.05; Others are not significant (p>.05). *Error%* denotes how much fluctuation exist in the results. *BF10* stands for Bayes Factor compared to a null model.

Discussion

Firstly, the results showed how the model's components could be well differentiated by political views depending on the country. In this situation, policies in cultures with high polarization should understand that cooperative actions in the COVID-19, such as avoiding crowded places, can be highly politicized, leading to consequences in the social and institutional system (Bartusevicius et al., 2021). Nevertheless, working with the different segments of society may be necessary for integrative and coordinated actions since social dilemmas would need to be solved by general and mutual cooperation (Fujii, 2003).

Secondly, regarding Taiwan and Japan, we verified that political differences might not affect the actual behavior in these countries. However, it may affect Japan's efforts to adopt new habits, social expectations, attitudes, feelings of moral obligation, and fear, reflecting the partisan's differences in supporting and expecting measures against COVID-19 (Liff, 2021). Moreover, the data also shows that even in places with controlled COVID-19 cases or specific political stability, as it can be seen for Taipei city and Tokyo, respectively, this may not guarantee trust in governmental's policies for all parties. Also, the overall trust may still not be significant. Thus, showing how the pandemic can be dependently related to general dissatisfaction with governmental authorities.

Finally, in Brazil, the significant differences with great effect sizes in almost all the components can be reflected by the rising in political polarization. This political scenario may impact trust in health policies, feelings of moral obligation, fear, and behavior. Right-wing partisans tend to oppose restrictive measures more due to their belief system against public spending and the restriction of economic and business activities (Ramos et al., 2020). Moreover, the differences between Liberals and Republicans may play in the same sense for some estimates in New York City, where Republicans may be more sensitive to the economic consequences of COVID-19 (Bruine et al., 2020). Of course, these differences have much less magnitude than in Brazil. However, Republicans would still tend to fear contagion less,

behave less, and hold less intention to practice social distancing, besides trust more than liberals in health policies by the former President Trump administration. These findings are also supported by previous research (Clinton et al., 2021; Bruine et al., 2020).

Conclusion

Overview and remarks for each city

This study presented significant contributions for policymakers by showing that social and cognitive factors can bring significant changes in the variance of efforts and reported behavior of avoiding crowded places. Moreover, as an international contribution of the study, this variance can be significantly different by the city where people live or the political position they belong. Therefore, attention to these factors is necessary to understand human behavior in the COVID-19 pandemic and future health crises. Also, by looking at each city, idiosyncratic conclusions can be generated while making comparisons across them.

In Tokyo, although the relationship among the variables can have a tangible impact on behavioral change, its general mean scores are still low compared to the explained variance and respectively scores in the City of New York and Brasilia, revealing how communications and campaigns can get much more benefit from integrating the contents of this study. Also, it is essential to notice that even though Japan may present years of political stability, differences in the measures by political positions can still produce effects almost similar to cities such as in New York, which could be a reflection of some groups` judgment on the government's indecisive response to COVID-19 due to considerations over the business, economics and the Olympics (Liff, 2021).

Taipei showed a less variance explanation of the model than other countries, resulting from the success in controlling the pandemic. This would make the effect of each component on intentions or behavior reasonably non-necessary to exist. But still, explained variance of fear was the highest in this country. We reported that the predictors of fear were better

predictors in countries with controlled situations. Because of that, we assume that the constant contact with public health crises may diminish their effects on fear. However, by looking at the mean scores of the components, it is possible to verify that fear, intentions, behavior, attitudes, injunctive norms, and other components are still positive. They also do not differ so much from Tokyo, for example, or even New York in some cases. This could be due to consciousness about the seriousness of COVID-19 made through previous experience with SARS, high population density that may be sensitive to outbreaks, and proactive policies by the government (Summers et al., 2020). From political differences in this country, we should also mention the effect on trust in authorities, which may suffer differences in judgment by parties, even if the country has a controlled situation over COVID-19.

It was possible to predict reasonably well the behavior in New York City. The estimates of this city present similarities in injunctive norm to intention and perceived behavioral control to behavior like in Tokyo, but it may also show likeness with Brazil in fear due to significant clusters of infection by data collection. Nevertheless, New York City plays in a relatively middle position among the four cities in most of the mean scores of the components. Furthermore, political differences in the components were mainly mediated by the contrast between liberals and republicans, as expected from political polarization.

Brasilia was the city with the most explained variance in behavior, holding the highest scores in the components compared to the other cities, except for the trust. Thus, policies may be well effective if they adopt the components of the model. Nevertheless, political polarization can be a significant concern for controlling social distance since some parties may present tendencies for noncooperative behavior with high differences from others. Previous research showed that resistance to support COVID-19 measures by practicing social distance might be due to Brazil's principles and beliefs of political orientation. This is because conservatives consider businesses and industries as key societal institutions while

opposing public spending, where measures of social distancing and financial assistance would mainly threaten it (Ramos et al., 2020). Important to mention, in addition, that Brazil's economy was at risk, inflation, public debt, and recession worsened by the COVID-19 pandemic[10].

Implication for policy-making

Policymakers should consider psychological strategies, especially in communications, to increase cooperation by understanding the differences and influences of the variables of this research. Examples of potential interventions would be: (1) highlighting positive benefits of the behavior, especially showing evidences and in a tone of request for cooperation, while giving space for citizens opinions (Ajzen, 1991; Fujii, 2003); (2) creating means for people to understand the social expectation by their peers, their government and their referent people, such as celebrities, to not be at crowded places (e.g. images of them in crowded areas can give the wrong social expectation) (Cialdini & Goldstein, 2004); (3) targeting feelings of moral obligation by giving awareness about people in need such as populations with high risks, showing the actions to prevent bad outcomes to them, while emphasizing one's ability to do it and finally indicating their responsibility to become involved (Schwartz, 1977); (4) helping citizens by facilitating their behavior and giving them a sense of controllability over it; (5) understanding the role of intention as a motivation for plan on how, when and where the behavior can occur in citizens` life, thus information on these directions is needed to be included in communications (Fujii, 2003) or feedback for correcting bias, while helping them with better choices (Thaler, et al. 2013); (6) reducing political polarization and understanding that in communities divided by it, different response to certain factors is expected, thus attention to each group is needed, especially understanding their belief's system; and (7) understanding that people may rely also on emotions, such as fear and feelings of moral

[10] The World Bank in Brazil, 2021

obligation in order to make decisions (Slovic, 2010). However, knowing that even if there is no coping or instructional information in communications that would guide people to adopt the behavior to reduce these emotional arousals, no attitudinal or behavioral change can be expected (Fujii, 2003; Leventhal et al., 1967). Finally, as quoted by the past environmental psychologist and consultant of UNESCO and IAEA, Professor Terence Lee: "*Research results make people think - they are not sufficiently trusted by our sponsors to make them dash out to apply solutions"* (Uzzell, 2015). Thus, we expect this research to foment discussions and debates between policymakers and researchers before any immediate application while also considering our communities' well-being, safety, and freedom.

Limitations and future agenda

About research limitations in this study, firstly, there is a need to amplify the sample in each country if policymakers would like to expand the interpretation for their different political positions with the model proposed in the first section since the allocation of all the political groups would remain the study with a low number of a participant for each one. Secondly, although some effects in the model can be considered equal across the cities in this study, replication of data in other cultures or cities in the same countries is needed before considering some effects as reasonably universal. Thirdly, the researchers point out the need to consider the specificities of each location for better interpretation, besides the need for experimental, qualitative, and interdisciplinary studies for a clear understanding of the phenomenon of this research. Thus, a multimethod and interdisciplinary approach can facilitate the comprehension of the gaps in this study. Finally, data collection was conducted differently in Brazil using snowball sampling due to the national regulations, where participants are not allowed to be paid.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Barros, M. N. D., Aguiar, M. M., Carvalho, F., Macedo, A., & Pereira, A. T. (2021). COVID-19 Fear Scale-Validation and adaptation for the perinatal period. *Journal of Human Growth and Development*, *31*(1), 9-17. http://dx.doi.org/10.36311/jhgd.v31.11546.

Bartusevicius, H., Bor, A., Jørgensen, F., & Bang, M. (2021). The psychological burden of the COVID-19 pandemic is associated with anti-systemic attitudes and political violence.

Bentler, P. M. (1992). On the fit of models to covariances and methodology to the Bulletin. *Psychological Bulletin*, *112*(3), 400. https://doi.org/10.1037/0033-2909.112.3.400

Brazilian Institute of Geography and Statistics. Cities and States. Retrieved 26, September 2021 from https://www.ibge.gov.br/en/cities-and-states/df/brasilia.html\

Bruine de Bruin, W., Saw, HW. & Goldman, D.P. Political polarization in U.S. residents' COVID-19 risk perceptions, policy preferences, and protective behaviors. *J Risk Uncertain* **61,** 177–194 (2020). https://doi.org/10.1007/s11166-020-09336-3

Byrne, B. M. (2013). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. Routledge. https://doi.org/10.4324/9780203807644

Cialdini, R. B., & Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annu. Rev. Psychol.*, *55*, 591-621. https://doi.org/10.1146/annurev.psych.55.090902.142015

Clinton, J., Cohen, J., Lapinski, J., & Trussler, M. (2021). Partisan pandemic: How partisanship and public health concerns affect individuals' social mobility during COVID-19. *Science advances*, *7*(2), eabd7204. https://doi.org/10.1146/10.1126/sciadv.abd7204

Chan, L., & Bishop, B. (2013). A moral basis for recycling: Extending the theory of planned behaviour. *Journal of Environmental Psychology*, *36*, 96-102. https://doi.org/10.1016/j.jenvp.2013.07.010

Cheng, Cindy, Joan Barceló, Allison Hartnett, Robert Kubinec, and Luca Messerschmidt. 2020. COVID-19 Government Response Event Dataset (CoronaNet v1.0). *Nature Human Behaviour* (2020). https://doi.org/10.1038/s41562-020-0909-7

Costa, C., & Lee, S. (2019). The evolution of urban spatial structure in Brasília: Focusing on the role of urban development policies. *Sustainability*, *11*(2), 553.

Cvetkovich, G. (2013). *Social trust and the management of risk*. Routledge.

Das, A. K., Abdul Kader Jilani, M. M., Uddin, M. S., Uddin, M. A., & Ghosh, A. K. (2021). Fighting ahead: adoption of social distancing in COVID-19 outbreak through the lens of the theory of planned behavior. *Journal of Human Behavior in the Social Environment*, *31*(1-4), 373-393. https://doi.org/10.1080/10911359.2020.1833804

Dawes, R. M. (1980). Social dilemmas. *Annual review of psychology*, *31*(1), 169-193.

Delacre, M., Leys, C., Mora, Y. L., & Lakens, D. (2019). Taking parametric assumptions seriously: Arguments for the use of Welch's F-test instead of the classical F-test in one-way ANOVA. *International Review of Social Psychology*, *32*(1). http://doi.org/10.5334/irsp.198

Department of Urban Development, Taipei City Government. Taiwan Statistics. Retrieved November 11, 2021 from https://english.udd.gov.taipei/News_Content.aspx?n=D775B547B0EE179A&sms=49BD433E6C6E4A5B&s=DD5A46C4BB7D3B33

De Waal, F. B. (2008). Putting the altruism back into altruism: the evolution of empathy. *Annu. Rev. Psychol.*, *59*, 279-300. http://doi.org/10.5334/irsp.198

Dryhurst, S., Schneider, C. R., Kerr, J., Freeman, A. L., Recchia, G., Van Der Bles, A. M., ... & van der Linden, S. (2020). Risk perceptions of COVID-19 around the world. *Journal of Risk Research*, *23*(7-8), 994-1006. https://doi.org/10.1080/13669877.2020.1758193

Fan, C. W., Chen, I. H., Ko, N. Y., Yen, C. F., Lin, C. Y., Griffiths, M. D., & Pakpour, A. H. (2021). Extended theory of planned behavior in explaining the intention to COVID-19

vaccination uptake among mainland Chinese university students: an online survey study. *Human Vaccines & Immunotherapeutics*, 1-8. https://doi.org/10.1080/21645515.2021.1933687

Fischer R, Karl JA. Predicting Behavioral Intentions to Prevent or Mitigate COVID-19: A Cross-Cultural Meta-Analysis of Attitudes, Norms, and Perceived Behavioral Control Effects. *Social Psychological and Personality Science*. June 2021. https://doi.org/10.31234/osf.io/ek69g

Foster, K. R., Wenseleers, T., & Ratnieks, F. L. (2006). Kin selection is the key to altruism. *Trends in ecology & evolution*, *21*(2), 57-60. https://doi.org/10.1016/j.tree.2005.11.020

Frounfelker, R. L., Santavicca, T., Li, Z. Y., Miconi, D., Venkatesh, V., & Rousseau, C. (2021). COVID-19 Experiences and Social Distancing: Insights From the Theory of Planned Behavior. *American Journal of Health Promotion*. https://doi.org/10.1177/08901171211020997

Fujii, S. (2003). Prescription for Social Dilemmas. *Nakanishiya Pub., Kyoto*.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263-292.

Kerr, J., Panagopoulos, C., & van der Linden, S. (2021). Political polarization on COVID-19 pandemic response in the United States. *Personality and Individual Differences*, *179*, 110892. https://doi.org/10.1016/j.paid.2021.110892

Kohlberg, L., & Hersh, R. H. (1977). Moral development: A review of the theory. *Theory into practice*, *16*(2), 53-59. https://doi.org/10.1080/00405847709542675

Kondo, K. (2020). How Will Covid-19 Reshape Cities in Japan? Cover Story Number 6. *Research Institute of Economy, Trade and Industry Newspapers & Magazines*. Retrieved November 2, 2021 from https://www.rieti.go.jp/en/papers/contribution/kondo-

keisuke/01.html

Lankevich, George. "New York City". *Encyclopedia Britannica*, October 23 2020, https://www.britannica.com/place/New-York-City. Accessed September 26 2021.

Leventhal, H., Watts, J. C., & Pagano, F. (1967). Effects of fear and instructions on how to cope with danger. *Journal of personality and social psychology*, *6*(3), 313. https://doi.org/10.1037/h0021222

Liff, A. P. (2021). Japan in 2020: COVID-19 and the End of the Abe Era. *Asian Survey*, *61*(1), 49-64. https://doi.org/10.1525/as.2021.61.1.49

Lin, C. Y., Imani, V., Majd, N. R., Ghasemi, Z., Griffiths, M. D., Hamilton, K., ... & Pakpour, A. H. (2020). Using an integrated social cognition model to predict COVID-19 preventive behaviors. *British journal of health psychology*, *25*(4), 981-1005. https://doi.org/10.1111/bjhp.12465

Ly, A., Verhagen, J., & Wagenmakers, E. J. (2016). Harold Jeffreys's default Bayes factor hypothesis tests: Explanation, extension, and application in psychology. *Journal of Mathematical Psychology*, *72*, 19-32. https://doi.org/10.1016/j.jmp.2015.06.004

Marden, J. I. (2000). Hypothesis testing: from p values to Bayes factors. *Journal of the American Statistical Association*, *95*(452), 1316-1320. https://doi.org/10.1080/01621459.2000.10474339

Mao, Y., Chen, H., Wang, Y., Chen, S., Gao, J., Dai, J., Jia, Y., Xiao, Q., Zheng, P. and Fu, H., 2021. How can the uptake of preventive behavior during the COVID-19 outbreak be improved? An online survey of 4827 Chinese residents. *BMJ Open*, *11*(2), p.e042954.

McEachan, R. R. C., Conner, M., Taylor, N. J., & Lawton, R. J. (2011). Prospective prediction of health-related behaviors with the theory of planned behavior: A meta-analysis. *Health psychology review*, *5*(2), 97-144. https://doi.org/10.1080/17437199.2010.521684

New York State. Governor Cuomo Announces New York Ending COVID-19 State Disaster Emergency on June 24. News. Retrieved October 11, 2021 from https://www.governor.ny.gov/news/governor-cuomo-announces-new-york-ending-covid-19-state-disaster-emergency-june-24

Ng, K. H., & Kemp, R. (2020). Understanding and reducing the fear of COVID-19. *Journal of Zhejiang University. Science. B*, *21*(9), 752. https://doi.org/10.1136/bmjopen-2020-042954

Haidt, J. (2012). *The righteous mind: Why good people are divided by politics and religion*. Vintage.

Henrich, J., Boyd, R., Bowles, S., Camerer, C., Fehr, E., Gintis, H., ... & Tracer, D. (2005). "Economic man" in cross-cultural perspective: Behavioral experiments in 15 small-scale societies. *Behavioral and brain sciences*, *28*(6), 795-855. https://doi.org/10.1017/S0140525X05000142

Hofstede, G. (2011). Dimensionalizing cultures: The Hofstede model in context. *Online readings in psychology and culture*, *2*(1), 2307-0919. https://doi.org/10.9707/2307-0919.1014

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Parker, D., Manstead, A. S., & Stradling, S. G. (1995). Extending the theory of planned behaviour: The role of personal norm. *British journal of social psychology*, *34*(2), 127-138. https://doi.org/10.1111/j.2044-8309.1995.tb01053.x

Pew Research Center. The Partisan Divide on Political Values Grows Even Wider: Sharp shift among democrats on aid to needy, race, immigration. Political Parties. Retrieved on September 27 2021 from https://www.pewresearch.org/politics/2017/10/05/the-partisan-divide-on-political-values-grows-even-wider/.

Pfattheicher, S., Nockur, L., Böhm, R., Sassenrath, C., & Petersen, M. B. (2020). The emotional path to action: Empathy promotes physical distancing and wearing of face masks during the COVID-19 pandemic. *Psychological Science*, *31*(11), 1363-1373. https://doi.org/10.1177/0956797620964422

Prasetyo, Y. T., Castillo, A. M., Salonga, L. J., Sia, J. A., & Seneta, J. A. (2020). Factors affecting perceived effectiveness of COVID-19 prevention measures among Filipinos during enhanced community quarantine in Luzon, Philippines: Integrating Protection Motivation Theory and extended Theory of Planned Behavior. *International journal of infectious diseases*, *99*, 312-323. https://doi.org/10.1016/j.ijid.2020.07.074

Public Security Secretary of the Federal District. Painel COVID-10 no Distrito Federal. COVID-19- Transparência. Retrieved July 9, 2021 from https://covid19.ssp.df.gov.br/extensions/covid19/covid19.html#/

Ramos, G., Vieites, Y., Jacob, J., & Andrade, E. B. (2020). Political orientation and support for social distancing during the COVID-19 pandemic: evidence from Brazil. *Revista de Administração Pública*, *54*, 697-713. https://doi.org/10.1590/0034-761220200162x.

Schwartz, S. H. (1977). Normative influences on altruism. In *Advances in experimental social psychology* (Vol. 10, pp. 221-279). Academic Press.

Shmueli, L. (2021). Predicting intention to receive COVID-19 vaccine among the general population using the health belief model and the theory of planned behavior model. *BMC Public Health*, *21*(1), 1-13. https://doi.org/10.1186/s12889-021-10816-7

Slovic, P., Finucane, M. L., Peters, E., & MacGregor, D. G. (2007). The affect heuristic. *European journal of operational research*, *177*(3), 1333-1352. https://doi.org/10.1016/j.ejor.2005.04.006

Slovic, P. (2010). If I look at the mass I will never act: Psychic numbing and genocide. In *Emotions and risky technologies* (pp. 37-59). Springer, Dordrecht.

https://doi.org/10.1007/978-90-481-8647-1_3. Available by Scholars` Bank, University of Oregon. Retrieved 29, September 2021 from https://scholarsbank.uoregon.edu/xmlui/handle/1794/22103.

Statistics Bureau of Japan. Population Census. E-Stat: Portal Site of Official Statistics of Japan. Retrieved September 27 2021 from https://www.e-stat.go.jp/en/stat-search/files?page=1&layout=datalist&toukei=00200521&tstat=000001136464&cycle=0&year=20200&month=24101210&tclass1=000001136465&tclass2=000001154388

Summers, J., Cheng, H. Y., Lin, H. H., Barnard, L. T., Kvalsvig, A., Wilson, N., & Baker, M. G. (2020). Potential lessons from the Taiwan and New Zealand health responses to the COVID-19 pandemic. *The Lancet Regional Health-Western Pacific*, 100044. https://doi.org/10.1016/j.lanwpc.2020.100044

Thaler, R. H., Sunstein, C. R., & Balz, J. P. (2013). Choice architecture. In *The behavioral foundations of public policy* (pp. 428-439). Princeton University Press. https://doi.org/10.1515/9781400845347-029

The New York Times. Tracking Coronavirus in New Tork City, N.Y. Retrieved August 3, 2021, from https://www.nytimes.com/interactive/2021/us/new-york-city-new-york-covid-cases.html

The World Bank, 2021. The World Bank in Brazi. Retrieved November 1, 2021, from https://www.worldbank.org/en/country/brazil/overview#1

Tokyo Metropolitan Government. Updates on COVID-19 in Tokyo. COVID-19 Information Website. Retrieved 27, September 2021 from Tokyo https://stopcovid19.metro.tokyo.lg.jp/en/.

Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology*, *5*(2), 207-232. https://doi.org/10.1016/0010-0285(73)90033-9

United States Census Bureau. 2019 American Community Survey 1-Year Estimates. Retrieved September 26, 2021 from https://data.census.gov/cedsci/profile?g=1600000US3651000

Uzzell, D. (2015). Obituary: Terry Lee. *Journal of Environmental Psychology*, *44*, 160-161. https://doi.org/10.1016/j.jenvp.2015.05.005

Wang, A. H. E. (2019). The myth of polarization among Taiwanese voters: The missing middle. *Journal of East Asian Studies*, *19*(3), 275-287.

Wang, C. J., Ng, C. Y., & Brook, R. H. (2020). Response to COVID-19 in Taiwan: big data analytics, new technology, and proactive testing. *Jama*, *323*(14), 1341-1342. https://doi.org/10.1001/jama.2020.3151

Wolff, K. (2021). COVID-19 Vaccination Intentions: The Theory of Planned Behavior, Optimistic Bias, and Anticipated Regret. *Frontiers in Psychology*, *12*. https://10.3389/fpsyg.2021.648289

World Health Organization, 2021. COVID-19: Vulnerable and high-risk groups. *WHO International.* Retrieved on October 31, 2021, from https://www.who.int/westernpacific/emergencies/covid-19/information/high-risk-groups

Yabe, T., Tsubouchi, K., Fujiwara, N., Wada, T., Sekimoto, Y., & Ukkusuri, S. V. (2020). Non-compulsory measures sufficiently reduced human mobility in Tokyo during the COVID-19 epidemic. *Scientific reports, Nature*, *10*(1), 1-9. https://doi.org/10.1038/s41598-020-75033-5