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Short communication

COVID-19 vaccine preferences in India ☆

Prateek Bansal [a,*], Alok Raj [b], Dhirendra Mani Shukla [c], Naveen Sunder [d]

[a] Department of Civil and Environmental Engineering, National University of Singapore, Singapore
[b] Operations & Decision Sciences, XLRI Xavier School of Management, Jamshedpur, India
[c] Business Policy and Strategy, Indian Institute of Management, Udaipur, India
[d] Department of Economics, Bentley University, Waltham, MA, USA

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A B S T R A C T

India's mass vaccination efforts have been slow due to high levels of vaccine hesitancy. This study uses data from an online discrete choice experiment with 1371 respondents to rigorously examine the factors shaping vaccine preference in the country. We find that vaccine efficacy, presence of side effects, protection duration, distance to vaccination centre and vaccination rates within social network play a critical role in determining vaccine demand. We apply a non-parametric model to uncover heterogeneity in the effects of these factors. We derive two novel insights from this analysis. First, even though, on average, domestically developed vaccines are preferred, around 30% of the sample favours foreign-developed vaccines. Second, vaccine preference of around 15% of the sample is highly sensitive to the presence of side effects and vaccination uptake among their peer group. These results provide insights for the ongoing policy debate around vaccine adoption in India.

1. Introduction

India, the context that we investigate in the current study, is the country with the second-highest incidence of COVID-19 with more than 34 million cases and over 480,000 deaths as of early January 2022 [32]. The Indian government has tried to prevent the spread of the virus through measures such as mask mandates, lockdowns, and mass vaccination. There have been four major national lockdowns, in addition to numerous other state and local ones [27]. These lockdowns have controlled virus transmission, but they have also been accompanied by economic losses, social distress [29] and increase in domestic violence [21].

While a combination of interventions are needed to curb the spread of the coronavirus, mass vaccination efforts hold the greatest promise for bringing an end to the current pandemic [25,16]. However, vaccination rates in India remain low in comparison to other countries across the globe, with only around 44% of Indians being fully vaccinated [2]. In addition to supply side challenges related to vaccine procurement, prioritization, and distribution [14], there are several demand-side factors that have hindered vaccination efforts [18,28]. Recent studies suggest that vaccine hesitancy is one of the main hurdles across the globe [11,20,25]. Vaccine hesitancy, estimated to be between 29 and 42% [12], is potentially the primary driver of low vaccination rates in India. Hence, there is an urgent need to understand characteristics shaping preferences for the COVID-19 vaccine in the Indian context.

A few recent studies have explored the preferences of Indians towards the safety and effectiveness of COVID-19 vaccine [8,19,26], but they do not quantify the effect of that various vaccine attributes have on preferences related to vaccines. Our analysis plugs this gap in the literature and is one of the first detailed investigations of the factors affecting COVID-19 vaccine preferences in India. Using a Discrete Choice Experiment (DCE), we quantify the sensitivity of consumers' vaccine preference relative to changes in various attributes such as efficacy, protection duration, side effects, price and administration location. Finally, we explore heterogeneities in the effectiveness of drivers of vaccine preferences using a non-parametric empirical model. Such a demand-side analysis is timely and critical because countries need to ramp up vaccination efforts in the face of the emergence of new variants. The findings of our study have the potential to shape ongoing policy discussions in India and other developing countries.

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* Corresponding author.
E-mail address: prateekb@nus.edu.sg (P. Bansal).

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2. Experiment design and data collection

2.1. Sample and data collection

The data for this study comes from an online discrete choice experiment (DCE) conducted between May and June 2021.[1] The respondents were recruited from a panel enlisted by MarketXcel, a market research agency in India. The sample consists of individuals who are (i) above 18 years of age, (ii) have not yet received COVID-19 vaccine, and (iii) residing in one of the following five states – Maharashtra, Tamil Nadu, Uttar Pradesh, West Bengal, and Delhi. These states were chosen because they represent approximately 41% of the Indian population (as per Census 2011), and accounted for a disproportionately high number of COVID-19 cases/deaths in the country.[2] We use a quota sampling approach, where respondents were stratified based on gender, marital status, and age. In total, we received 1675 responses, but the final analysis sample consists of 1371 observations – we removed 304 observations because the survey completion time was <3.5 min (that is, half of the median survey completion time). The summary statistics are presented in Table 1 – male, single, and younger age groups are overrepresented in our sample.

2.2. Experiment design

DCEs are widely applied in health economics to study the trade-offs between attributes in individual-level preferences for health services [4,31]. More recently, DCEs have also been used to study the factors affecting the uptake of COVID-19 vaccine [15,5].

In this study, we also use a DCE design, where the selection of attributes is guided by a thorough literature review. The review suggests that the prominent factors affecting consumer preferences for COVID-19 vaccine are – prevalence side effects [3,6,17,22], the origin of developer/manufacturer [5,25], place of administration [15,9], efficacy against the virus [22,13], out-of-pocket costs [3,15], duration of protection [5], number of doses required [9], vaccine adoption in social networks [22], source of COVID-19 related information [22,7]. We include a bulk of these attributes in our experiment.[3] The levels of the attributes are chosen such that (i) they span the entire attribute support, and (ii) vaccine profiles are comparable to the ones that were available at the time of the experiment in India.[4] Table 2 presents details on the attributes that were included in our experiment.

In the experiment, respondents were asked to choose their preferred vaccine between two alternatives based on vaccine attributes. Given the number of alternatives and the possible levels of different attributes, a full-factorial design would have meant a total of over 1.3 million choice scenarios $(2^3 \times 4^2 \times 3^2)^2$. Since it is infeasible to present all these choice scenarios, we generated a DCE design using the D-efficient experimental design approach with zero priors [10,23]. The aim of the D-efficient design is to create a subset of all possible choice scenarios that optimize a function (e.g., minimises the determinant) of the asymptotic variance–covariance matrix, i.e. generate choice data that could result in the highest possible confidence in the parameter estimates for a given sample size. Our experiment consists of six blocks with six choice scenarios per block, and each respondent was shown a randomly selected block.[5] In each scenario, a respondent was asked that "based on this information, which COVID-19 vaccine would you prefer to uptake?" An example choice scenario is presented in Table 3.

3. Empirical strategy

We use a conditional logit (CL) model to estimate the effect of attributes on the preference for COVID-19 vaccine. The indirect utility under this specification can be expressed as:

$$U_{itj} = \boldsymbol{x}_{itj}^{'}\boldsymbol{\delta} + \varepsilon_{itj}. \tag{1}$$

In Eq. (1), U_{itj} is the indirect utility of individual i from choosing vaccine j in choice scenario t, $\boldsymbol{\delta}$ is the vector of marginal utilities pertaining to the corresponding attribute vector $\boldsymbol{x}_{itj}$ (listed in Table 3), and ε_{itj} is idiosyncratic error term with standard Gumbel distribution. Thus, individual i's probability of choosing alternative j in choice scenario t is:

$$Pr_{itj} = \frac{\exp(U_{itj})}{\sum_{\forall k}\exp(U_{itk})} \tag{2}$$

Additionally, we quantify the unobserved heterogeneity in main effects across different parts of the population using a non-parametric logit mixed logit (LML) model [1,30]. The indirect utility in the LML specification is:

$$U_{itj} = \boldsymbol{x}_{itj}^{'}\boldsymbol{\delta} + \boldsymbol{w}_{itj}^{R\,'}\boldsymbol{\beta}_i^R + \varepsilon_{itj}. \tag{3}$$

A key point of departure from the CL model is that the LML specification contains random parameters $(\boldsymbol{\beta}_i^R)$, which are assumed to have a discrete mixing distribution over their finite support set Ω (or multi-dimensional grid). The joint probability mass function of random parameters in LML is specified as follows:

$$\Pr(\boldsymbol{\beta}_i^R = \boldsymbol{\beta}_{\boldsymbol{r}}^R) = \frac{\exp\left[\boldsymbol{z}(\boldsymbol{\beta}_{\boldsymbol{r}}^R)^{'}\boldsymbol{\alpha}\right]}{\sum_{s\in\Omega}\exp\left[\boldsymbol{z}(\boldsymbol{\beta}_{\boldsymbol{s}}^R)^{'}\boldsymbol{\alpha}\right]} \tag{4}$$

In Eq. (4), $\boldsymbol{z}(\boldsymbol{\beta}_{\boldsymbol{r}}^R)$ is assumed to be a spline function, and $\boldsymbol{\alpha}$ is the corresponding vector of parameters. The LML model is estimated using maximum simulated likelihood estimator, which is described in Bansal et al. [1]. Standard errors are obtained using bootstrapping.

4. Results

The results from the CL model (columns 1–2, Table 4) indicate that vaccine efficacy and side effects are critical determinants of preferences for COVID-19 vaccine. The odds of accepting a vaccine with 90% or higher effectiveness is 1.26 times higher than one with 80% effectiveness. Individuals also have a higher likelihood of choosing a vaccine with no side effects (odds ratio = 1.35), and a longer duration of protective effects (odds ratio = 1.16). We show that Indian consumers have a lower probability of picking a vaccine developed outside of India (odds ratio = 0.93), while their odds of getting the vaccine when all of their peer group has been fully vaccinated is, on average, 1.41 times higher than those with an entirely unvaccinated peer group.

We further probe for heterogeneities in the observed results using a non-parametric LML model. Instead of a single coefficient

[1] The study was approved by the Institutional Review Board at the Indian Institute of Management Udaipur, India (Ref. IIMU2105241A).

[2] These states have accounted for a combined total of over 13 million cases and 200 thousand deaths as on 3rd January 2022, which is more than countries such as France, Italy, and Canada.

[3] The number of doses and information about vaccines are not included because these attributes are not as relevant in the Indian context.

[4] At the time of the survey, there were three vaccines that had been approved for use and had been deployed in India – Covishield, Covaxin and Sputnik.

[5] There is no consensus in the literature against including or excluding the opt-out alternative [24]. To circumvent potential misinterpretation of the opt-out alternative and avoid modelling challenges arising from a zero-level alternative, we do not present it to respondents. If we were interested in welfare estimation, an opt-out alternative could have been included.

Table 1
Demographic and spatial distribution across sample and population (N = 1371).

Attributes	Sample	2011 Indian census	State (Zone)	Sample	Total number of confirmed cases (In millions, June 14, 2021)
Age			Maharashtra (West)	23%	5.98
18–39 year	69%	57%	Tamil Nadu (South)	23%	2.43
40–60 year	23%	32%	Uttar Pradesh (North)	15%	1.70
Above 60 year	8%	11%	West Bengal (East)	19%	1.48
Marital Status			Delhi (North)	20%	1.43
Single	32%	21%			
Married	66%	78%			
Other	2%	1%			
Gender					
Male	59%	51%			
Female	41%	49%			

Table 2
Attribute levels in the DCE.

Attributes	Levels
Effectiveness of vaccine	80%
	More than 90%
Developer	Domestic
	Imported
Out-of-pocket cost	INR 0
	INR 400 (US$5.4)
	INR 800 (US$10.8)
	INR 1200 (US$16.2)
Side effects	No side effect Fever or headache
Duration of protection	6 months
	12 months
	18 months
	24 months
Place of vaccine administration	At a government hospital
	At a private hospital
	At your home
The proportion of friends and family members who has taken the vaccine	10%
	50%
	90%

Table 3
An example of the choice situation presented to respondents.

	Vaccine 1	Vaccine 2
Effectiveness of vaccine	80%	More than 90%
Vaccine developer	Domestic	Imported
Purchase price	₹ 1200	₹ 800
Side effects	Fever or headache	No side effect
Duration of protection	12 months	6 months
Place of vaccine administration	Home	Private hospital
The proportion of friends and familymembers who has taken the vaccine	10%	90%

Based on the above information, which COVID-19 vaccine would you prefer to uptake?
◯ Vaccine 1.
◯ Vaccine 2.

(CL estimates), the LML model provides a probability (cumulative) distribution function of the odds ratios – the results for each attribute are presented in Fig. 1. The graphs in Fig. 1 demonstrate that the distribution of odds ratio varies significantly from the CL estimate, although the mean odds ratio from the LML model are similar in magnitude to the CL estimates (see columns 2 and 5 of Table 1). The heterogeneity in effects, as visible in Fig. 1, are statistically confirmed by the significant estimates of standard deviations (column 4 in Table 4).

We uncover some important patterns from the LML estimates. Although the coefficient estimate of the CL model (column 1 of Table 4) suggests that there is a preference for vaccination at home, the cumulative distribution function (CDF) from LML in Fig. 1, however, indicates that 29.7% of individuals preferred vaccination in private/government hospitals. Note that the right vertical axis and blue curve in Fig. 1 represent the CDF of the odds ratios from LML. The CDF value at the odds ratio of 1 for vaccination at home is 0.297, which implies that 29.7% of individuals have an odds ratio below one for vaccination at home (i.e., they preferred vaccination in private/government hospitals over home). Similarly, CL results suggest a higher inclination of individuals towards domestically developed vaccines, but the CDF of odds ratios from LML shows that 68.8% of individuals preferred domestic vaccine and the remaining 31.2% preferred foreign-developed vaccines. The LML results also demonstrate that around 12% of the sample have odds ratio of the vaccinated social network above five, while around 17% have a strong preference for a vaccine with no side effects (odds ratios > 6), which are very different from the CL estimates.

5. Discussion and conclusions

The results from this study are largely congruent with recent evidence from other contexts – vaccine efficacy, ease of inoculation, social networks and presence of side effects are important determinants of preferences for COVID-19 vaccine (see [5,25]). An encouraging result from our analysis is that individuals are much more likely to choose a vaccine with more than 90% efficacy – at the time of the survey, two out of the three vaccines approved for use in India met this criterion.

Although the aggregate effects favour a domestically developed vaccine, we also demonstrate that there is a sizable part of the population (31.2%) that has a higher likelihood of selecting a foreign-developed vaccine. This suggests that giving individuals a choice regarding vaccine type can potentially increase uptake. This is important from a policy perspective since at the moment most facilities in India do not provide such a choice. Our findings also suggest that providing vaccines in people's homes might further increase uptake, which suggests that the government could plausibly increase door-to-door vaccination efforts, especially in locations with low health facility density. It is important that these efforts should complement, and not replace, the current strategy of vaccination at health centres – this is because our data suggest that a considerable proportion (30%) of the population still prefer to get vaccinated at hospitals.

Our results demonstrate that large sections of the population are concerned about vaccine side effects (17%) and are influenced by vaccine uptake among their peer group (12%). These subpopulations are critical because to reach herd immunity the Indian government has to tailor policies to cater to these potential *late adopters*. Examples of such policies include subsidized (or free) care to address any issues related to vaccine side effects, and effec-

Table 4
Results of conditional logit and logit mixed logit model (N = 1371).

Attributes	Conditional Logit		Logit Mixed Logit		
	(1) Coeff (Std. Err.)	(2) Odds ratio	(3) Mean of Coeff. (Std. Err.)	(4) Std. Dev. Of Coeff. (Std. Err.)	(5) Mean odds ratio
Alternative-specific constant	-0.322^{***} (0.026)		-0.353^{***} (0.031)		
90% or more effective (base: 80%)	0.231^{***} (0.024)	1.26	0.338^{***} (0.031)	0.237^{***} (0.030)	1.40
Foreign developer (base: domestic)	-0.072^{***} (0.024)	0.93	-0.067^{*} (0.041)	0.225^{***} (0.028)	0.94
Out of pocket cost (unit increase: INR 100)	-0.051^{***} (0.003)	0.95	-0.064^{***} (0.005)		0.94
No side effect (base: fever/headache)	0.301^{***} (0.024)	1.35	0.439^{***} (0.029)	0.687^{***} (0.040)	1.55
Protection duration (unit increase: 6 month)	0.148^{***} (0.014)	1.16	0.243^{***} (0.019)	0.306^{***} (0.036)	1.27
Vaccine administration at home (base: hospital)	0.089^{***} (0.029)	1.09	0.073^{*} (0.049)	0.349^{***} (0.053)	1.08
Vaccinated friends/family (base:0, unit increase: all)	0.341^{***} (0.044)	1.41	0.491^{***} (0.052)	0.537^{***} (0.042)	1.63
Loglikelihood	−5171.5		−5013.6		

** 0.01 < p-value < 0.05.
*** p-value < 0.01.
* 0.05 < p-value < 0.15.

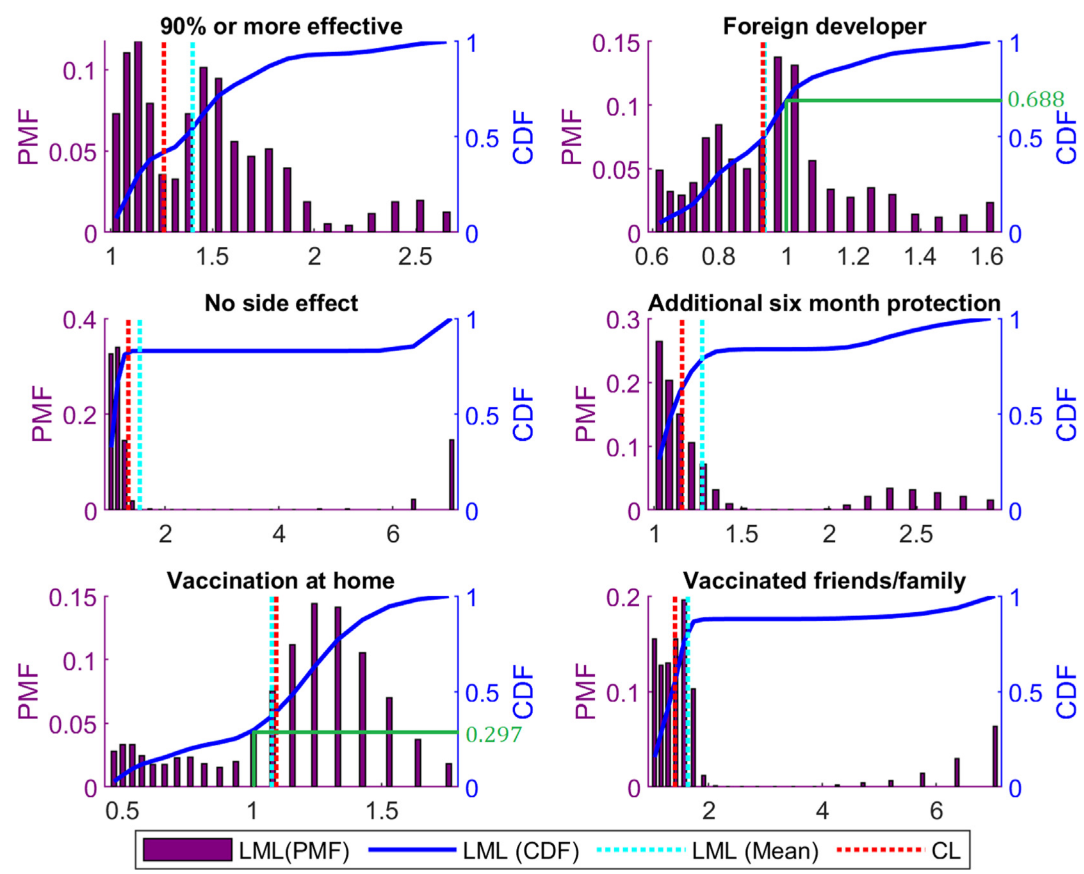

Fig. 1. The estimated distribution of odds ratios (LML: logit mixed logit, CL: conditional logit; PMF: probability mass function; CDF: cumulative distribution function).

tive communication strategies to demonstrate that the benefits of taking a vaccine significantly outweigh the risks.

This study has a few limitations. First, the survey was conducted in mid-2021, when the fully vaccinated population in India was below five percent, and the information about the side effects and effectiveness of the vaccine was limited. With about half of the Indian population being fully vaccinated at the beginning of 2022, an individual's intention to get vaccinated might have evolved with the first-hand information about the side effects and effectiveness of vaccines from vaccinated friends and relatives. Future research should consider possibilities of conducting repeated cross-section or panel studies to capture the evolving pandemic situation. Having said that, our study may be relevant to a large number of African countries where the vaccination rates are still in single digits.

Second, this study estimates the effect of only quantitative attributes on the individual's preference for COVID-19, but several attitudinal (e.g., trust in vaccine technology) and pandemic-related factors (e.g., hospitalization/death due to COVID-19 in one's social network) are not considered here. These omitted variables might induce biases in the parameters estimates. Future investigations might consider including questions to capture this kind of information to address omitted variable biases. Third, the data for the study comes from information collected using an internet-based survey– the usual caveats of such a data collection procedure applies to our study, especially that vulnerable demographic groups (e.g., old age group) with a lack of internet access might be underrepresented in this study.

Despite these limitations, the present study provides timely quantitative evidence on factors that shape vaccine preferences in India, one of the nations that is in dire need of ramping up vaccination efforts. It is also one of the first detailed studies of determinants of preferences for COVID-19 vaccines in the South Asian context and will contribute to policy discussions on ways to expedite COVID-19 vaccine delivery in the region.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Bansal P, Daziano RA, Achtnicht M. Extending the logit-mixed logit model for a combination of random and fixed parameters. J Choice Modell 2018;27:88–96.
[2] Bloomberg. More Than 9.26 Billion Shots Given: Covid-19 Tracker. Bloomberg.com. 2022. URL: https://rb.gy/kda5dv [accessed on January 5, 2022].
[3] Borriello A, Master D, Pellegrini A, Rose JM. Preferences for a COVID-19 vaccine in Australia. Vaccine 2021;39(3):473–9.
[4] Clark MD, Determann D, Petrou S, Moro D, de Bekker-Grob EW. Discrete choice experiments in health economics: a review of the literature. Pharmacoeconomics 2014;32(9):883–902.
[5] Dong D, Xu RH, Wong E-Y, Hung C-T, Feng DA, Feng Z, et al. Public preference for COVID-19 vaccines in China: A discrete choice experiment. Health Expect 2020;23(6):1543–78.
[6] El-Elimat T, AbuAlSamen MM, Almomani BA, Al-Sawalha NA, Alali FQ. Acceptance and attitudes toward COVID-19 vaccines: A cross-sectional study from Jordan. PloS One 2021;16:e0250555.
[7] Goruntla N et al. Predictors of acceptance and willingness to pay for the COVID-19 vaccine in the general public of India: A health belief model approach. Asian Pac J Trop Med 2021;14(4):165. https://doi.org/10.4103/1995-7645.312512.
[8] Jain J, Saurabh S, Goel AD, Gupta MK, Bhardwaj P, Raghav PR. COVID-19 vaccine hesitancy among undergraduate medical students: results from a nationwide survey in India. medRxiv 2021.
[9] Kreps S, Dasgupta N, Brownstein JS, Hswen Y, Kriner DL. Public attitudes toward COVID-19 vaccination: The role of vaccine attributes, incentives, and misinformation. npj Vaccines 2021;6:1–7.
[10] Kessels R, Goos P, Vandebroek M. A comparison of criteria to design efficient choice experiments. J Mark Res 2006;43(3):409–19.
[11] Kessels R, Luyten J, Tubeuf S. Willingness to get vaccinated against Covid-19 and attitudes toward vaccination in general. Vaccine 2021;39(33):4716–22.
[12] Lazarus JV, Ratzan SC, Palayew A, Gostin LO, Larson HJ, Rabin K, et al. A global survey of potential acceptance of a COVID-19 vaccine. Nat Med 2021;27(2):225–8.
[13] Leng A, Maitland E, Wang S, Nicholas S, Liu R, Wang J. Individual preferences for COVID-19 vaccination in China. Vaccine 2021;39(2):247–54.
[14] Luyten J, Tubeuf S, Kessels R. Rationing of a scarce life-saving resource: Public preferences for prioritizing COVID-19 vaccination. Health Econ 2021;31:342–62.
[15] McPhedran R, Toombs B. Efficacy or delivery? An online Discrete Choice Experiment to explore preferences for COVID-19 vaccines in the UK. Econ Lett 2021;200:109747. https://doi.org/10.1016/j.econlet.2021.109747.
[16] Moor SE, Tusubira AK, Akiteng AR, Hsieh E, Ngaruiya C, Rabin TL, et al. Development of a discrete choice experiment to understand patient preferences for diabetes and hypertension management in rural Uganda. Lancet Global Health 2020;8:S22. https://doi.org/10.1016/S2214-109X(20)30163-7.
[17] Mouter N, de Ruijter A, Ardine de Wit G, Lambooij MS, van Wijhe M, van Exel J, et al. "Please, you go first!" preferences for a COVID-19 vaccine among adults in the Netherlands. Soc Sci Med 2022;292:114626. https://doi.org/10.1016/j.socscimed.2021.114626.
[18] Pal R, Rathore U, Das U. Can states bring down vaccine prices? Yes, by coming together as a single buyer. The Indian Express. 2021. URL: https://indianexpress.com/article/opinion/columns/covid-19-second-wave-vaccination-price-shortage-7314175/ [accessed on January 5, 2022].
[19] Panda DS, Giri RK, Nagarajappa AK, Basha S. Covid-19 vaccine, acceptance, and concern of safety from public perspective in the state of Odisha. India Hum Vacc Immunotherap 2021;17(10):3333–7.
[20] Qin W, Wang E, Ni Z. Chinese consumers' willingness to get a COVID-19 vaccine and willingness to pay for it. PloS One 2021;16:e0250112.
[21] Ravindran S, Shah M. Unintended consequences of lockdowns: covid-19 and the shadow pandemic, No. w27562. National Bureau of Economic Research; 2020.
[22] Reiter PL, Pennell ML, Katz ML. Acceptability of a COVID-19 vaccine among adults in the United States: How many people would get vaccinated? Vaccine 2020;38(42):6500–7.
[23] Rose JM, Bliemer MCJ. Constructing efficient stated choice experimental designs. Transp Rev 2009;29(5):587–617.
[24] Ryan M, Skåtun D. Modelling non-demanders in choice experiments. Health Econ 2004;13(4):397–402.
[25] Schwarzinger M, Watson V, Arwidson P, Alla F, Luchini S. COVID-19 vaccine hesitancy in a representative working-age population in France: a survey experiment based on vaccine characteristics. Lancet Public Health 2021;6(4):e210–21.
[26] Sharun K, Rahman CKF, Haritha CV, Jose B, Tiwari R, Dhama K. Covid-19 vaccine acceptance: Beliefs and barriers associated with vaccination among the general population in India. J Exp Biol Agric Sci 2020;8(Spl-1-SARS-CoV-2):S210–8.
[27] Soni P. Effects of COVID-19 lockdown phases in India: an atmospheric perspective. Environ Dev Sustain 2021;23(8):12044–55.
[28] Tarfe A. How India's Covid-19 communication strategy is failing to combat vaccine hesitancy. Indian Express. 2021. URL https://indianexpress.com/article/opinion/how-indias-covid-19-communication-strategy-is-failing-to-combat-vaccine-hesitancy-7342890/ [accessed 22.06. 21].
[29] Taylor S, Paluszek MM, Rachor GS, McKay D, Asmundson GJG. Substance use and abuse, COVID-19-related distress, and disregard for social distancing: A network analysis. Addict Behav 2021;114:106754. https://doi.org/10.1016/j.addbeh.2020.106754.
[30] Train K. Mixed logit with a flexible mixing distribution. J Choice Modell 2016;19:40–53.
[31] Tarfe A. How India's Covid-19 communication strategy is failing to combat vaccine hesitancy. Indian Express. 2021. URL https://indianexpress.com/article/opinion/how-indias-covid-19-communication-strategy-is-failing-to-combat-vaccine-hesitancy-7342890/ [accessed 22.06. 21].
[32] World Health Organization. India: WHO Coronavirus Disease (COVID-19) Dashboard with Vaccination Data. 2022. URL: https://covid19.who.int [accessed on January 5, 2022].