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Rationing of a scarce life-saving resource: Public preferences for prioritizing COVID-19 vaccination

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Abstract

In the face of limited COVID-19 vaccine supply, governments have had to identify priority groups for vaccination. In October 2020, when it was still uncertain whether COVID-19 vaccines would be shown to work in trials, we conducted a discrete choice experiment and a best-worst ranking exercise on a representative sample of 2060 Belgians in order to elicit their views on how to set fair vaccination priorities. When asked directly, our respondents prioritized the groups that would later receive priority: essential workers, the elderly or those with pre-existing conditions. When priorities were elicited indirectly, through observing choices between individuals competing for a vaccine, different preferences emerged. The elderly were given lower priority and respondents divided within two clusters. While both clusters wanted to vaccinate the essential workers in the second place, one cluster ($N = 1058$) primarily wanted to target virus spreaders in order to control transmission whereas the other cluster ($N = 886$) wanted to prioritize those who were most at risk because of a pre-existing health condition. Other strategies to allocate a scarce resource such as using a "lottery", "first-come, first-served" approach or highest willingness-to-pay received little support.

KEYWORDS

COVID-19, discrete choice experiment, distribution, efficiency, equity, justice, priority, public preferences, scarcity, vaccine

1 | INTRODUCTION

From November 2020 onwards, several vaccines that protect against the *SARS-CoV-2* virus have become available (Bloom et al., 2020; Mahase, 2020; Mallapaty & Ledford, 2020). However, the initial supply was insufficient to vaccinate all (Wouters, Shadlen, Salcher-Konrad, et al., 2021) and throughout most of 2021 strict rationing has been required worldwide. First, there were problems of fairly distributing the vaccine internationally, across countries and continents (Emanuel, Persad, Kern, et al., 2020). Second, and this is the focus of this paper, at national levels, priority groups for vaccination needed to be designated (Emanuel, Persad, Upshur, et al., 2020; Persad et al., 2020; Schmidt, 2020; Subbaraman, 2020).

Almost unanimously, policy makers and expert groups selected the same groups for priority access: the highest risk categories – the elderly, those with pre-existing conditions, and essential workers, which include front-line health care professionals (CDC, 2020; European Commission, 2020; Gayle et al., 2020; JCVI, 2020; World Health Organization, 2020). Nonetheless, there could have been "reasonable disagreement" about ethical prioritization of a COVID-19 vaccine. As already illustrated earlier during the pandemic with scarcity of mechanical ventilation in intensive care units, how to ration a life-saving resource is never obvious (Emanuel, Persad, Upshur, et al., 2020; Liu et al., 2020; Persad et al., 2020; Roope et al., 2020). In the context of vaccines, fair rationing is even less straightforward because vaccines usually serve two separate functions: to prevent death and illness within the vaccinated individuals but also to reduce transmission toward others.

In this study, we investigated several allocative mechanisms to set vaccination priorities and their acceptability toward the general public. This is in the first place interesting from a scientific perspective. The circumstances of the pandemic present a unique research opportunity to investigate how people want to share a life-saving resource across the population. Their views are not elicited from an artificial, abstract context of scarcity, but from a concrete reality in which they are all directly involved parties. At the time of the survey, the circumstances allowed us to consider a sufficient level of abstraction; it was still unclear whether vaccines would become available at all, and if available, which properties and effectiveness they would have. This made it easier to focus on broad distributive principles regarding how to ration a critical resource, abstracting from issues such as side effects related to specific vaccines. Second, understanding the public's opinion is important for policy reasons as public involvement has already been highly instrumental in the COVID-19 pandemic for measures such as physical distancing, face masks or lockdowns to be effective (Chernozhukov et al., 2021; Mitze et al., 2020). In general, greater public and patient involvement in health care decisions, especially those with large stakes and a substantial ethical component, is increasingly considered important (Florin & Dixon, 2004).

Our first study objective was to ask a representative sample of the general population in Belgium to rank eight alternatives to distributing the first COVID-19 vaccines in their preferred order. Our second objective was to study further the respondents' preferences by letting them choose whom they would vaccinate over multiple pairs of concrete individuals competing for a vaccine. We finally summarize the overall preferences in a choice model that allowed us to calculate a vaccine priority score for specific population subgroups. What we found is that, when asked directly, people confirmed the three subgroups that policy makers eventually selected of highest priority: those with pre-existing conditions, essential workers and the elderly. However, when we elicited their priorities through observing actual priority setting choices between individuals, high virus spreaders were given higher priority, while elderly received lower priority. We also identified two clusters of respondents: one that wanted to target those individuals who spread the virus, and the other that wanted to target those who are worst-off through pre-existing conditions.

The paper proceeds as follows. Section 2 provides a summary of the previous literature. Section 3 describes the design of the survey and the two experiments and presents the methods for data analysis. Section 4 displays the results. Finally, we provide some concluding remarks.

2 | BACKGROUND

Empirical evidence on public preferences toward COVID-19 vaccines was inexistent at the time of our survey and remains scarce. While Borriello et al. (2021) collected the preferences of Australians regarding hypothetical COVID-19 vaccines, their study did not focus on vaccine allocation but described vaccines according to seven attributes (i.e., incidence of mild and major side effects, effectiveness, mode of administration, location of administration, time to availability and cost). Public preferences in COVID-19 vaccine allocation strategies were examined in Gollust et al. (2020) where a sample of 1004 adults representative of the US population were asked to indicate among eight alternative groups based on age, health risk and employment type whom should receive high, medium, or low priority to vaccination. They found that respondents had a high willingness to allocate vaccines to front-line medical workers, essential non-medical workers, high-risk children, and older adults.

More recently, preferences of US adults' regarding vaccine prioritization were analyzed as part of two surveys (Persad et al., 2021); they both showed that people would prioritize health care workers and adults of any age with serious comorbidity among their top four priority groups. Healthy older adults were however not ranked within highest priority groups to vaccination, especially among older respondents. Most respondents were in agreement with the phased allocation strategy proposed by the National Academies of Science, Engineering, and Medicine (CDC, 2020) but placed a lower priority on vaccinating healthy older adults. Finally, an online conjoint experiment in 13 countries was carried out to identify preferences for different vaccine prioritization schemes based on five attributes (occupation, age, coronavirus transmission status, risk of death from COVID-19 and income) and between three and eight levels (Duch et al., 2021). This large-scale study showed that most countries favored access to vaccines to individuals at higher risk of COVID-19 death and higher risk of COVID-19 transmission, to essential workers and non-essential workers unable to work from home, to older individuals and to individuals in low-income categories.

Our study adds to this literature. It provides a unique ranking exercise of allocation strategies including priority groups along with standard strategies used in the context of scarce resources allocation. It also provides a discrete choice experiment (DCE) for COVID-19 vaccine allocation at national level comparing hypothetical individuals described on five key attributes.

3 | METHODS

3.1 | Sample and survey

We used a nationally representative panel of the market research agency Dynata to complete a survey between October 6, 2020 and October 16, 2020.[1] A sample of 2698 respondents drawn from a panel of 5500 selected members who mirror the Belgian population (aged 18–80 years) as well as possible,[2] were invited to participate in the survey. Of these, 494 did not complete the survey and 144 were excluded because they did not meet the company's internal quality controls (e.g., they completed the survey unreasonably fast: below a third of the median time to completion). This left us with a sample of 2060 respondents, which fulfilled pre-determined Belgium quota for age, gender, level of education and province.

The survey[3] first asked respondents for a range of sociodemographic characteristics along with their financial situation, general health status, attitudes toward vaccination and toward the government's handling of the corona crisis, whether they had had COVID-19, whether someone they knew had had it, had been hospitalized or died because of it. Respondents were also asked whether their profession was among the “essential professions” (i.e., those that were obliged to keep working during the first “lockdown” in March/April 2020) and whether they considered themselves to be part of a risk group for COVID-19 and if so, which group they belonged to (i.e., old age, chronic illness, obesity, or other). The questionnaire was then followed with an explanation of the background to the study where we explicitly asked the respondents to think about what they considered fairest to society when allocating the limited first supply of COVID-19 vaccines, and not to choose simply what would be most advantageous to themselves. After the ranking exercise and the choice experiment, respondents were asked about whom should decide who gets the COVID-19 vaccine first (government, scientists or the population), whether they would choose to be vaccinated themselves once a vaccine becomes available, and how easy they found answering the survey.

3.2 | Ranking exercise

We presented the respondents with eight alternative strategies to distribute the COVID-19 vaccines summarized in Table 1. Each strategy was presented one after the other using successive new screens that respondents were only able to progress from every 10 s. The eight strategies were then summarized as a list in their short version (with the possibility to go back to the full explanation if needed) and respondents were asked to rank all of them from “most suitable” to “least suitable” according to their opinion. They were told that the vaccine was equally safe and effective in all people and that they should think about what would be the best allocation not for their self-interest but for the society as a whole.

3.3 | Discrete choice experiment

We then subjected respondents to a DCE. This is a widely used survey method to study individuals' preferences, especially in health care settings (Louviere et al., 2000; Ryan et al., 2008) including patients prioritization (Bryan & Dolan, 2004; Diederich et al., 2012; Luyten et al., 2015, 2019; Ratcliffe et al., 2009). Participants are presented with a series of choice sets, consisting of two or more products or services that are described by the same attributes with differing attribute levels. By observing a large number of choices, researchers can infer how attributes and levels implicitly determine the value of the good under evaluation. Here, we asked respondents to choose whom they would vaccinate from two hypothetical people candidates to the COVID-19 vaccine. Both candidates were described with identical attributes, but they differed in the levels of these attributes so that we could infer how important these attributes were to the respondents when prioritizing one or the other candidate for vaccination.

TABLE 1 Eight strategies to distribute a COVID-19 vaccine

Strategy (in short)	Full explanation as presented in the experiment
Prioritizing chronically ill	We could first give the vaccine to people who are medically most at risk of serious illness and death because they have another underlying condition: Cancer patients, people with lung disease, heart disease, kidney disease, severe obesity, etc. By vaccinating them first, we would protect **the people most vulnerable to the virus**.
Prioritizing the elderly	We could first give the vaccine to people over 60 years old. We know that, on average, these people run a much higher risk of serious illness or death from a corona infection. By vaccinating them first, we would protect **the people most vulnerable to the virus**.
Prioritizing spreaders	We could first give the vaccine to the people who spread the virus the most because they have a lot of social contacts in their daily life (at work, at school, in their neighborhood, in public transport, etc.). These people themselves are not at high risk of serious illness or death from COVID-19, but they can infect many others. By vaccinating them first, we would **slow down the spread of the virus as much as possible**.
Prioritizing workers	People who work will cause a greater economic cost when they become ill than those who do not work. By first vaccinating working people, we would ensure that the virus does **as little further damage as possible to the economy**.
Prioritizing essential professions	Some professions are more "essential" to society than others. During the pandemic, health workers, hospital staff, police and garbage services had to continue working as usual, while others had to work from home or were temporarily unemployed. By prioritizing workers from these vital sectors, we would protect the **normal functioning of society**.
Lottery	We could distribute the available vaccines randomly among the population, for example through a lottery. Therefore, each individual would have the **same chance to be vaccinated**, regardless of their health risk or the social impact of an infection.
First-come, first-served	We could distribute the available vaccines to the population according to the principle "**first-come, first-served.**" People who present themselves the fastest for vaccination at the doctor, pharmacy or government would be given priority from the moment there is a vaccine.
Market	We could sell the available vaccines to the highest bidder. The people **who want to pay the most money** for a vaccine would be given priority.

3.3.1 | Attributes and levels

The DCE focused on the five attributes of people that are considered most relevant by experts (Liu et al., 2020; Persad et al., 2020; Roope et al., 2020) as well as policy institutions (European Commission, 2020; Gayle et al., 2020; World Health Organization, 2020) to claim to priority: (1) their age, (2) whether they belonged to a medically vulnerable group due to pre-existing conditions (e.g., diabetes, cancer, HIV, cardiovascular disease, obesity, etc.), (3) their cost to the economy if COVID-19 infected, (4) whether their profession is considered "essential" (e.g., health care workers, policemen, firemen, etc.), and (5) whether they would spread the virus to many or few other people in case of infection (see Table 2). The remaining strategies used in the ranking exercise (lottery, market, first-come first-served) were excluded from the DCE.

3.3.2 | Design

We designed the DCE using "partial profiles", that is, we kept the levels of two attributes constant between the two candidate profiles and only varied the levels of three attributes (Kessels, Jones, & Goos, 2011, 2015). We colored the varying levels of each profile to make them stand out in the choice sets (Jonker et al., 2019). An example of a choice set appears in Figure 1. Varying the levels of only three attributes and highlighting them made the choice tasks easier to perform and therefore respondents' choices more consistent and valid for the analysis.[4] Respondents even testified that despite the choice problem had been quite difficult, it had been doable thanks to the design strategy. Because the varying attributes differed between choice sets, the partial profile design also helped prevent respondents from using lexicographic decision rules, by which profile alternatives are first compared on the most important attribute, then on the second most important attribute, and so forth, until one profile remains. If one or more dominant attributes are held constant, respondents can trade off the remaining attributes more easily, and not divert to non-compensatory decision-making. The statistical

TABLE 2 Attributes and levels used in the DCE

Attribute	Levels
Medical risk group	- Someone who has no underlying conditions
	- Someone who has higher risk through chronic illness
Age	- Someone who is younger than 60 years
	- Someone who is at least 60
Virus spreader	- In case of infection, someone who is expected to contaminate 1 other person
	- In case of infection, someone who is expected to contaminate 10 other persons
Cost to society	- In case of infection, someone who is expected to cost society 0 € per day
	- In case of infection, someone who is expected to cost society 100 € per day
	- In case of infection, someone who is expected to cost society 1000 € per day
Essential profession	- Someone who has a profession that is considered “essential”
	- Someone who has a profession that is considered not “essential”

Abbreviation: DCE, discrete choice experiment.

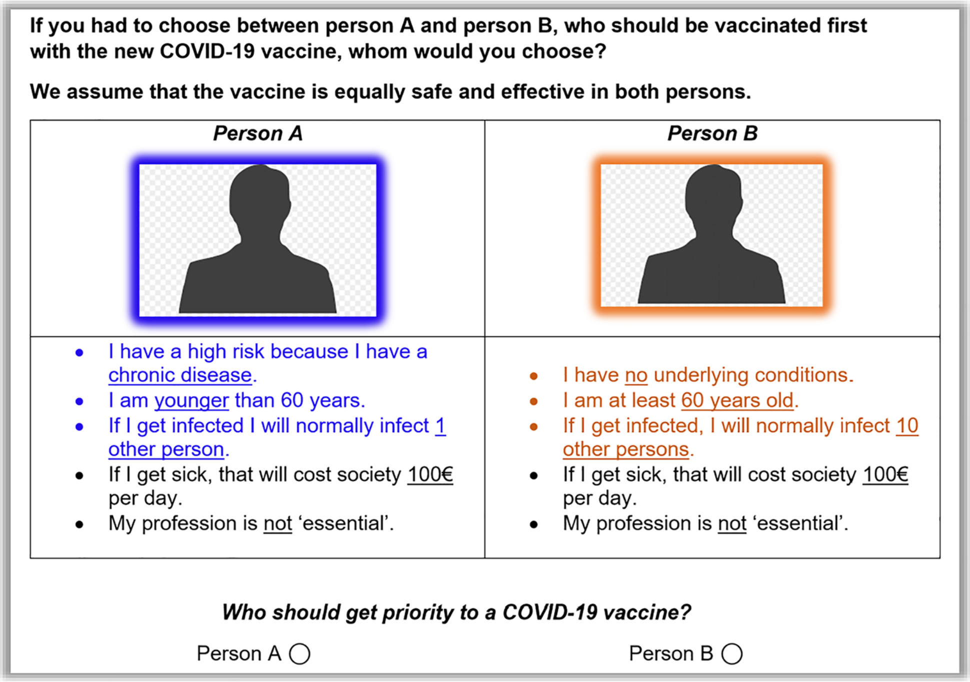

FIGURE 1 Example of a choice set [Colour figure can be viewed at wileyonlinelibrary.com]

efficiency of a partial profile design is, however, reduced compared to a full profile design, in which all attributes can vary in the choice sets, but this is generally offset by more consistent choices (Louviere et al., 2008).

The statistical design or the specific composition of the choice profiles we generated was “D-optimal” within a Bayesian framework (Kessels, Jones, Goos, & Vandebroek, 2011). A D-optimal design makes it possible to examine the importance of the attributes and their levels with maximum precision. The Bayesian addition means that prior information is taken into account in the design generating process so that choice sets with a dominant profile are largely avoided (Crabbe & Vandebroek, 2012). The complete design of the DCE consisted of 30 choice sets that we split into three different blocks of 10 choice sets and was efficiently constructed to estimate all two-way interaction effects between the attributes (see Appendix B for the design and the design generating process). A representative sample of respondents were assigned in three similar groups to each of the three blocks. The 10 choice sets of each survey were presented in a random order to counteract a possible order effect of the choice sets. At the start of the DCE, we presented the respondents with a mock choice set that was identical to the last choice set in their survey and allowed us to analyze consistency in their choices.

We first tested various visualizations among a convenience sample ($N = 10$) and then carried out a pilot study of the full survey in 174 respondents. After correcting for a few minor issues, we went ahead with the full launch of the study in 2060 respondents.

3.4 | Statistical analysis

We analyzed the choice data by estimating a panel mixed logit (PML) model using the hierarchical Bayes technique in the JMP Pro 16 Choice platform (based on 10,000 iterations, with the last 5000 used for estimation; SAS Institute Inc.). This model assumes normally distributed utility parameters over the respondents to accommodate unobserved heterogeneity in the respondents' preferences. The mean utility function is thereby the sum of the mean attribute effects (Train, 2009).

We first estimated a PML model for the entire sample and then investigated the heterogeneity in the individual utility estimates by comparing the subject standard deviations to the mean attribute effects. These subject standard deviations were of the same size or even larger than the mean estimates, indicating the need to identify respondent segments. We therefore clustered the individual utility estimates from the PML model using Ward's hierarchical cluster analysis and estimated separate PML models for each cluster. This second-stage PML analysis for every cluster allows revealing differing and even opposing preferences between clusters (if there are). This procedure with a post-estimation cluster analysis has already shown its merits in a DCE measuring public preferences for vaccination programs (Luyten et al., 2019) and a DCE predicting the uptake of the COVID-19 digital contact-tracing app (Mouter et al., 2021).

To verify the cluster formation, we estimated latent class models with different numbers of classes using the *lclogit2* package in Stata 17 (Yoo, 2020) as a more direct alternative to the two-step PML procedure. A latent class model assumes a discrete distribution for the heterogeneous utility parameters instead of the normal distribution underlying the PML analysis. By relaxing the normality assumption, a latent class model allows capturing multimodal utility distributions directly in the event of diverging or opposing preferences between respondents. This model is therefore particularly suited in the context of segmented samples of respondents (Goossens et al., 2014). Louviere (2006) recommended to use latent class models more frequently because they would often fit the data at least as good as PML models and are easy to interpret.

Once we distinguished clear and meaningful respondent segments, we characterized them through bivariate chi-square analyses on the respondents' covariates and multiple logistic regression with the cluster membership as response variable and the respondents' covariates as explanatory variables. In all our analyses, we used a significance threshold of 5%.

4 | RESULTS

On average, the 2060 respondents took 29 min to complete the survey. The median completion time was 15 min, with the interquartile range between 13 and 20 min. When asked how difficult completion of the survey was, only 21 respondents (1%) indicated it was "too difficult" whereas 1154 (56%) found it "easy" and 43% "difficult but doable." A sample of 1577 respondents (77%) gave the same answer twice to the repeated choice set, however differing answers do not point at invalid answers as the strength of preferences can be weak in this context. We observed that 116 respondents (6%) gave the same answer throughout the DCE and are therefore called "straightliners." As their number is considerable and their answers unlikely to match their choices, we followed standard practice in excluding these straightliners as a way of caution not to lower the quality of the data (Johnson et al., 2019; Sandorf, 2019). This left us with 1944 respondents for the analysis.

Overall, the analysis sample included 39% of respondents considering themselves part of a specific COVID-19 risk group. A minority (<20%) of the sample experienced a COVID-19 infection themselves or in their immediate proximity. A majority (59%) reported being dissatisfied with the government's approach to the crisis. A large majority of respondents (78%) thought that the vaccine allocation decision should ultimately be determined by scientists; 10% thought the government should decide and 12% thought that it should be the population only. When asked whether they would become vaccinated with a COVID-19 vaccine, 74% responded affirmatively (see Table 3).

TABLE 3 Sample characteristics

Variables	Categories	*N*	Percentage (%)
Respondents' general background			
Gender	Female	993	51
	Male	951	49
Age	18–24	194	10
	25–34	330	17
	35–44	331	17
	45–54	379	19
	55–64	321	17
	65–80	389	20
Language	Dutch	1112	57
	French	832	43
Province	Vlaams-Brabant	191	10
	Brabant Wallon	129	7
	Brussels Capital	176	9
	Antwerpen	288	15
	Limburg	157	8
	East Flanders	249	13
	West Flanders	200	10
	Hainaut	115	6
	Liège	186	10
	Luxembourg	102	5
	Namur	151	8
Education	None	7	0
	Primary school	61	3
	First degree secondary school	187	10
	Second degree secondary school	247	13
	Third degree secondary school	684	35
	Higher education (non-university)	468	24
	University or post-university education	268	14
	PhD	14	1
	Other	8	0
Have children	Yes	1213	62
	No	731	38
Profession	Working	978	50
	Homemaker	80	4
	Student	158	8
	Unemployed	129	7
	Disabled	127	7
	Retired	472	24

TABLE 3 (Continued)

Variables	Categories	N	Percentage (%)
Difficulties with monthly expenses	Never	802	41
	Once a year	422	22
	Once every 3 months	391	20
	Every month	329	17
Self-assessed health	Very good	248	14
	Good	741	41
	Rather good	602	34
	Bad	167	9
	Very bad	22	1
	Don't know/don't want to say	14	1
Respondents' COVID-19 related background			
Self-reported membership of a COVID-19 risk group	No	1183	61
	Yes, elderly	366	19
	Yes, chronically ill	400	21
	Yes, severe obesity	124	6
	Yes, other	68	3
Self-reported profession is labeled as "essential"	Yes	367	19
	No	1577	81
Has had a COVID-19 infection	Yes, confirmed with a test	57	3
	Probably, but not confirmed with a test	160	8
	No	1727	89
Know personally someone who has had COVID-19	Yes, confirmed with a test	293	15
	Probably, but not confirmed with a test	175	9
	No	1476	76
Know personally someone who was hospitalized for COVID-19	Yes	118	6
	No	1826	94
Know personally someone who died of COVID-19	Yes	83	4
	No	1861	96
Satisfaction with government's approach to COVID-19 pandemic	Very satisfied	58	3
	Rather satisfied	729	38
	Rather dissatisfied	787	40
	Very dissatisfied	370	19
Determination of the vaccine prioritization strategy	Population	221	12
	Government	175	10
	Scientists	1398	78
COVID-19 vaccine acceptance once the vaccine is available and considered safe and effective by the authorities	Yes, sure	624	35
	Yes, probably	698	39
	No, probably not	322	18
	No, sure not	150	8

4.1 | Ranking exercise results

The ranking exercise results are summarized in Figures 2 and 3. Figure 2 uses cumulative distribution functions to synthesize how each strategy was ordered by the respondents. There was not one single strategy that dominated and was considered as best by a large majority. The eight strategies were clearly divided into three groups: three dominant

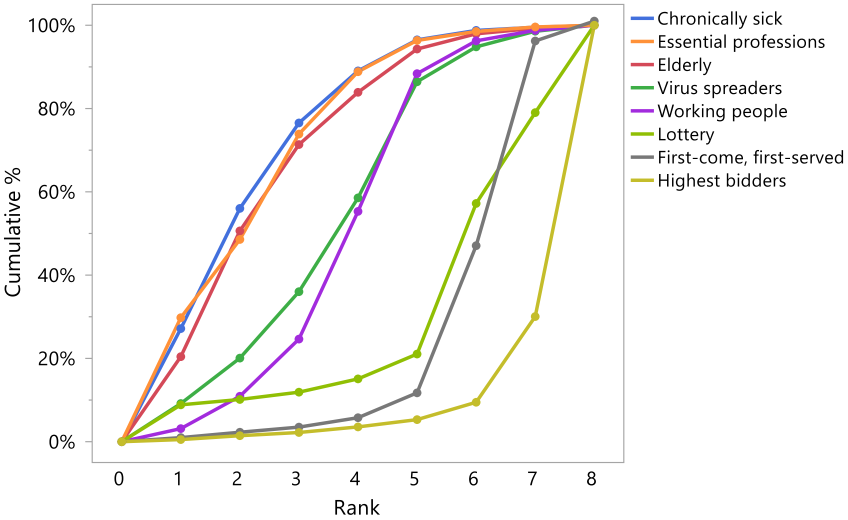

FIGURE 2 Cumulative distribution functions of alternative COVID-19 vaccine allocation strategies ranked from "most suitable" (rank of 1) to "least suitable" (rank of 8) [Colour figure can be viewed at wileyonlinelibrary.com]

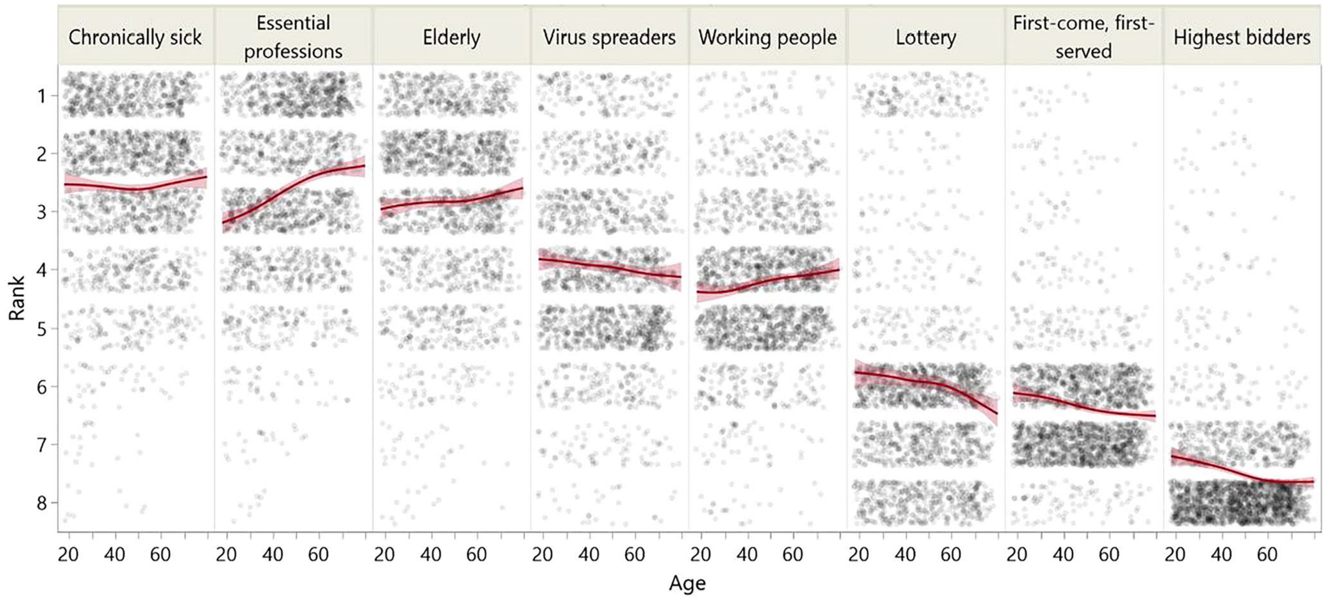

FIGURE 3 Scatterplot of the ranks of prioritization strategies along with their relationship to age summarized by a regression spline. The graph plots the ranking of each prioritization strategy according to age. Dots toward the left- and right-hand side are rankings of younger and older respondents, respectively. A darker zone around a rank shows the most observed ranking of that strategy. Note that the dots have been uniformly shifted up and down within each rank to avoid over-plotting (uniform jitter). The red lines summarize for each strategy the relationship between the ranking and the age of the respondent. For example, younger respondents ranked essential professions lower than older respondents as a preferred vaccination strategy [Colour figure can be viewed at wileyonlinelibrary.com]

strategies, two strategies ranked somewhere in the middle, and three strategies ranked in the three worst strategies. Prioritizing essential workers, chronically ill and elderly were found to be the three most supported strategies. On the other hand, market, lottery or "first-come, first-served" strategies were clearly the least preferred strategies with at least 80% of the respondents ranking them at the bottom of the ranking. Finally, targeting spreaders or protecting the economy were strategies ranked in the middle.

Figure 3 shows that the attractiveness of strategies was to some extent age-dependent. Although the overall ranking of strategies was mostly similar across age groups, when compared to younger respondents, older respondents ranked essential professions, elderly and workers higher while younger respondents ranked vaccinating spreaders or alternative strategies such as lottery, first-come first-served or markets higher. While the lottery strategy was very unpopular across age groups (79% ranked it in the top three of worst strategies), one in 10 respondents thought that this was a very good strategy and ranked it as the most or second most suitable strategy for allocating vaccines in the population.

4.2 | DCE results

In total, we analyzed 19,440 choices between hypothetical individuals competing for vaccination. We first estimated a PML model in the five attributes and all possible two-way interactions between them. All interactions were, however, insignificant or negligible compared to the attribute main effects. Hence, main-effects model A (see Table 4 and Figure 4) summarizes the average preferences of the whole sample over the five attributes. This model shows that no single attribute dominated the other attributes. Instead, we found that three attributes were of large importance: belonging to a medically vulnerable group due to pre-existing conditions, having an "essential profession" and being a relatively large spreader of the virus. Both age and cost to society were of statistical significance with higher priority for older and more costly people but these effects were limited. While older people are also labeled as higher risk groups with COVID-19, being in an older age group was not found to be a strong predictor of vaccine priority by the public. Whether people would be costly to society if they had COVID-19 did not seem to matter much either.

Model A with the average preferences showed a large amount of subject heterogeneity and could therefore be misleading in case a population is polarized. This phenomenon is referred to as Simpson's paradox (Simpson, 1951). That is why we investigated individual preferences differences among respondents in a post-estimation cluster analysis, revealing two large clusters within the sample. The preferences of the first cluster ($N = 1058$ respondents, 54%) are summarized by model B. This cluster was in favor of prioritizing high virus-spreaders. The second cluster ($N = 886$ respondents, 46%), summarized in model C, prioritized vaccinating people with underlying conditions. Both clusters valued essential professions as the second most important attribute. Interestingly however, whereas people aged 60 or more were prioritized in the third place in cluster 2, they were not prioritized in cluster 1. Cluster 1 also valued people who were economically important whereas this attribute was statistically insignificant in cluster 2. Figure 4 presents the utility effects of all three models in predicting respondents' choices.

Because a latent class analysis could be a more direct alternative to the cluster analysis on the individual preferences and preferences could be more diverse or segmented than estimated using PML models, we also estimated latent class models to validate our results (see Appendix C). The selected two-class model revealed two latent classes with preferences comparable to those observed in the clusters from the cluster analysis. The first and second latent classes corresponded to clusters 1 and 2, containing 53% and 47% of the sample, respectively.

We analyzed whether there were any individual characteristics associated with membership to either cluster (see Table 5). Compared to those from cluster 2, members of cluster 1 were more likely to be French-speaking, to be in doubt about whether or not they should become vaccinated with a COVID-19 vaccine, to think that priorities must be set by the population (instead of by scientists or government), to be unemployed and to have had a COVID-19 infection that was not test-confirmed. There was no relationship between being a member of clusters 1 or 2 and respondents' age, having an "essential" profession, financial situation, level of education or other variables in our survey. If we consider that a safe and effective COVID-19 vaccine was seen as the only way out of the pandemic and that a majority of respondents (74%) reported they would probably or definitely become vaccinated, this absence of relationship suggests that respondents' choices in the experimentation were not driven by self-interest.

The PML models that we estimated for the full sample and the two clusters allow us to construct a concrete priority ranking of individuals described in terms of the five attributes we used. To compare the rankings across the different models, we rescaled the total utilities of the individual profiles for each model onto a desirability index ranging from 0 to 1 (or from 0 to 100%). Table 6 presents out of the 48 different profiles that were investigated, the profiles of individuals who would get highest and lowest priority along with the profiles where the differences in the rankings obtained for cluster 1 versus cluster 2 were the largest. The most attractive profile to be first vaccinated according to the full sample is profile A: someone who is part of a medical risk group, older than 60, who is likely to be a high virus spreader, with an economic cost of 1000 € per day in case of illness and who has an essential profession. The least attractive profile was the exact opposite: profile N. When comparing the two clusters, cluster 1 clearly exhibited a likelihood to rank older people with a lower priority, for example, profile C was the most attractive profile to be first vaccinated. The largest gap between the desirability indices between clusters 1 and 2 was observed in profile G. In Figure 5 we show the correlation between the desirability indices of the 48 different profiles according to each of the two clusters and pin-point the profiles that were the most outspoken with their letter.

TABLE 4 Panel mixed logit model estimates for the entire sample and the two clusters

Term	Model A ($N = 1944$)					Model B ($N = 1058$)					Model C ($N = 886$)				
	Posterior mean	Posterior standard deviation	Subject standard deviation	Lower 95%	Upper 95%	Posterior mean	Posterior standard deviation	Subject standard deviation	Lower 95%	Upper 95%	Posterior mean	Posterior standard deviation	Subject standard deviation	Lower 95%	Upper 95%
Medical risk group															
Yes	0.676**	0.024	0.446	0.632	0.724	0.309**	0.023	0.072	0.265	0.352	1.394**	0.060	0.547	1.276	1.521
No	−0.676**	0.024	0.446	−0.724	−0.632	−0.309**	0.023	0.072	−0.352	−0.265	−1.394**	0.060	0.547	−1.521	−1.276
Older than 60															
Yes	0.093**	0.015	0.442	0.064	0.124	−0.202**	0.017	0.291	−0.236	−0.169	0.504**	0.029	0.438	0.449	0.564
No	−0.093**	0.015	0.442	−0.124	−0.064	0.202**	0.017	0.291	0.169	0.236	−0.504**	0.029	0.438	−0.564	−0.449
Virus spreader															
10 other persons	0.660**	0.024	0.468	0.614	0.708	0.911**	0.032	0.477	0.849	0.973	0.480**	0.037	0.125	0.409	0.562
1 other person	−0.660**	0.024	0.468	−0.708	−0.614	−0.911**	0.032	0.477	−0.973	−0.849	−0.480**	0.037	0.125	−0.562	−0.409
Cost to society															
0 € per day	−0.123*	0.026	0.251	−0.173	−0.078	−0.334**	0.032	0.273	−0.400	−0.275	−0.050	0.033	0.130	−0.119	0.014
100 € per day	−0.011*	0.022	0.146	−0.054	0.030	0.060**	0.029	0.224	0.002	0.114	0.004	0.039	0.221	−0.071	0.072
1000 € per day	0.134*	0.027	0.262	0.082	0.187	0.274**	0.030	0.298	0.213	0.334	0.046	0.042	0.240	−0.039	0.129
Essential profession															
Yes	0.567**	0.019	0.519	0.529	0.604	0.362**	0.020	0.381	0.323	0.402	0.975**	0.046	0.737	0.886	1.071
No	−0.567**	0.019	0.519	−0.604	−0.529	−0.362**	0.020	0.381	−0.402	−0.323	−0.975**	0.046	0.737	−1.071	−0.886

** and * Significant at $p < 0.001$ and $p < 0.05$, respectively.

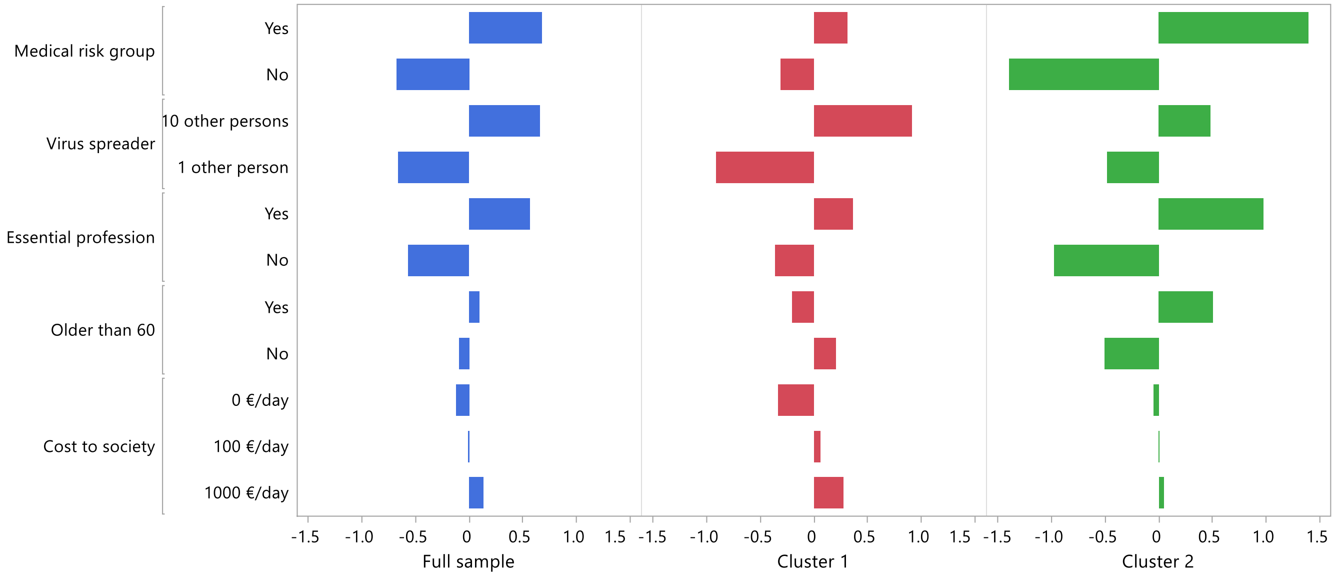

FIGURE 4 Estimated utilities of the full sample ($N = 1944$ respondents), cluster 1 ($N = 1058$ respondents), and cluster 2 ($N = 886$ respondents) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Multiple logistic regression model for classifying a person in cluster 1 versus cluster 2 based on relevant respondent characteristics and opinions, ranked from most important to least important

Term	Estimate	Chi-square	*p*-Value Chi-square	*p*-Value LR chi-square
Language				
Dutch	−0.384	56.212	0.000	0.000
French	0.384	56.212	0.000	
COVID-19 vaccine acceptance				
Yes, sure	−0.190	5.002	0.025	0.012
Yes, probably	0.054	0.428	0.513	
No, probably not	0.261	6.367	0.012	
No, sure not	−0.124	0.823	0.364	
Determination vaccine prioritization				
Population	0.321	8.086	0.004	0.015
Government	−0.281	5.761	0.016	
Scientists	−0.040	0.246	0.620	
Profession				
Unemployed	0.227	4.800	0.028	0.026
Not unemployed	−0.227	4.800	0.028	
Know personally someone who has had COVID-19				
Yes, confirmed with a test	−0.247	5.793	0.016	0.032
Probably, but not confirmed with a test	0.310	6.140	0.013	
No	−0.063	0.599	0.439	
Constant	0.534	17.024	0.000	0.000

TABLE 6 Ranking of individual profiles: the four most (A to D) and the four least (K to N) attractive profiles out of 48 options, and six profiles (E to J) with the largest difference in desirability between the clusters 1 and 2 respondents

	Attributes					Full sample		Cluster 1		Cluster 2	
Profile	Medical risk group	Older than 60	Virus spreader	Economic impact (€ per day)	Essential profession	Desirability index	Rank	Desirability index	Rank	Desirability index	Rank
A	Yes	Yes	Yes	1000	Yes	0.990	1	0.893	3	0.990	1
B	Yes	Yes	Yes	100	Yes	0.955	2	0.844	6	0.985	2
C	Yes	No	Yes	1000	Yes	0.946	3	0.990	1	0.844	6
D	Yes	Yes	Yes	0	Yes	0.931	4	0.747	11	0.977	3
E	Yes	Yes	No	100	Yes	0.651	13	0.411	30	0.846	5
F	No	No	Yes	1000	Yes	0.634	17	0.845	4	0.442	27
G	Yes	Yes	No	0	Yes	0.627	18	0.317	35	0.838	8
H	No	No	Yes	1000	No	0.373	31	0.670	15	0.161	42
I	Yes	Yes	No	0	No	0.366	32	0.150	45	0.558	23
J	No	No	Yes	100	No	0.339	36	0.622	18	0.156	43
K	No	No	No	1000	No	0.069	45	0.244	39	0.023	46
L	No	Yes	No	0	No	0.054	46	0.010	48	0.156	44
M	No	No	No	100	No	0.034	47	0.197	42	0.017	47
N	No	No	No	0	No	0.010	48	0.104	46	0.010	48

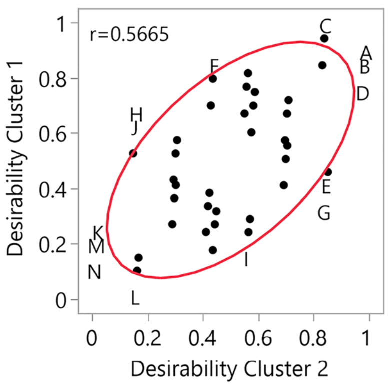

FIGURE 5 Scatterplot of desirability values of the 48 different profiles for cluster 1 versus cluster 2 where the four most attractive profiles (A to D) and the four least attractive profiles (K to N) are indicated along with profiles E to J that exhibit the largest difference in desirability indices between clusters 1 and 2 (see Table 6). Profiles with a letter fall outside the 75% density ellipse [Colour figure can be viewed at wileyonlinelibrary.com]

5 | DISCUSSION

This study shows how the population living in Belgium wanted to prioritize long-awaited COVID-19 vaccinations across the population at a time when widely diverging allocation strategies were possible. First, there was little support for libertarian-inspired approaches such as highest willingness-to-pay on a private vaccine market or "first-come, first served" strategies. A strict egalitarian approach like a lottery also received little support. Instead, the most supported strategies were those where priority groups were explicitly defined at a policy level.

Second, when asked to rank different vaccine allocation strategies, respondents would prioritize groups of the population similar to the ones that were eventually used and also identified in other studies (Duch et al., 2021; Gollust et al., 2020), namely targeting health workers and old and ill people at high risk of severe COVID-19 or death. However, as soon as we asked participants to make choices between hypothetical individuals after being provided with information about what being a high virus spreader or costly to society meant, their preferences leant toward a vaccination strategy simultaneously prioritizing medically vulnerable groups, high virus spreaders, and essential workers but no longer including older people as a priority group. This was also true for respondents from older age groups. This result is similar to Persad et al. (2020), who found that vaccinating healthy older adults was a lower priority in their study. Interestingly, the general public would also not prioritize for vaccination those who are of particular economic importance such as those who work.

Third, when trying to compare and rank within the three main target groups identified within the DCE, the population was divided in two clusters, each highlighting a separate function of vaccination. One share adhered to a strategy that we could label "utilitarian" since it would aim to maximize societal health outcomes by allocating vaccines strategically toward virus spreaders (cluster one) (Savulescu et al., 2020). These people also thought that vaccinating those with high economic cost to society was to some extent important. The other cluster adhered more toward a "prioritarian" strategy that put people who are at medically highest risk first (cluster two). Being a virus spreader or someone who could cost a lot to the economy was of little or no importance in this cluster. However, both groups considered essential professions a priority group but of secondary importance. Age was of minor importance in both groups; however prioritizing people older than 60 was positioned higher in the "prioritarian" group than in the "utilitarian" group where a slight priority was given to younger people. Such findings would be compatible with a "fair innings" argument according to which age is an accepted criterion for scarce health care resources allocation (Williams & Evans, 1997). It was not the case that membership of these clusters coincided with the characteristics of the respondents. For instance, there was no relationship between priority choices and being young (respectively old) or with having an essential profession or not. While respondents who were not working (students, retired or unemployed people and homemakers) were more likely to be part of the "utilitarian" cluster and those belonging to a COVID-19 higher risk group were more likely part of the "prioritarian" cluster, those correlations disappeared when multiple respondent characteristics were considered simultaneously.

Although by now there is an international policy consensus on the broad priority candidates to the COVID-19 vaccines, at the time when little information was available, many mechanisms to distribute vaccines were possible. As we showed, there was not an easy consensus in the general population. Depending on the method of surveying, that is, ranking options or discrete choices, our study shows that either elderly or virus spreaders were top-priority groups. Moreover, ranking within key groups was not straightforward either. This is nonetheless required as the identified priority groups constitute a sizable fraction of the population already, especially when risk groups or essential professions are defined broadly. The difficulty of defining a clear ranking among the identified priority groups has also been observed in the initial COVID-19 vaccination strategies put forward by the European Commission and World Health Organization Strategic Advisory Group of Experts on Immunization (European Commission, 2020; World Health Organization, 2020). Whereas these argued that when ranking between priority groups becomes unavoidable, risk groups should go first, the US National Academies of Sciences, Engineering, and Medicine argued to do the opposite and suggested giving the vaccine first to essential workers. Our experiment allowed us to construct a concrete ranking of individuals. However, such ranking was not based on membership to one particular group but on a combination of five characteristics. Rationing based on such an individual priority-score obtained over various relevant characteristics would be a more refined approach to priority setting than the current approach of selecting entire population subgroups but is less convenient for operational and political reasons.

Our study had the following limitations. One was the lack of a distinction within essential workers, especially since the health and social care workers have often been considered as top-priority groups. However, arguably, there is a different logic present in prioritizing health care workers versus other essential professions such as teachers or police. Another limitation was that, while our sample was broadly representative of the population in Belgium, it was recruited from an online panel where membership may be associated with unobserved characteristics (e.g., Internet access). In case these characteristics would translate into different preferences, our results would reflect these. Also, we investigated people's preferences for a hypothetical vaccine. However, the suitability of vaccination strategies obviously depends on the specific characteristics of the vaccine and these only become known when the vaccination program is fully rolled out. For instance, if the vaccine is less effective in older or immunocompromised individuals, it would be less desirable to prioritize these groups. Likewise, if the vaccine protects against severe COVID-19 symptoms but does not reduce contagion of others then a strategy targeting spreaders becomes useless. The weakness of our study is therefore to assume that the vaccine was simplistic and idealistic, that is, safe and effective in all population subgroups and simultaneously reducing symptoms and infectiousness.

A final note to conclude is that the importance given to public preferences is a matter of debate. It is undoubtedly important to include public opinion in a policy of large collective importance and in which there is interdependence between policy measures' effectiveness and public goodwill and participation. However, it does not mean that the public would like to define the norm: when asked who should ultimately get the mandate to determine priority groups, 78% of our respondents indicated scientists. Only about 10% stated that the population's preferences should be followed.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ETHICS STATEMENT

The Social and Societal Ethics Committee (SMEC) of KU Leuven decided that this study did not fall under the Belgian law on experiments as pseudonymized data collected by a third party were analyzed. No ethics approval was deemed necessary.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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ENDNOTES

[1] Our survey was carried out almost 1 month before the press release from Pfizer-BioNTech successfully completing their phase III trials for a COVID-19 vaccine (November 9, 2020).

[2] The research company has a pool of 252,597 volunteers, from which it selected a standard panel of 5500 individuals who resemble the Belgian population as good as possible. The company evaluates their pool of participants continuously, systematically eliminates low-quality responders and participation is rewarded with bonus points that lead to vouchers to buy certain products or make donations. Online panels are second-best in comparison with population surveys with randomly drawn participants from a census. However, we checked how our survey sample compared to national Belgium data (see Table A1 in Appendix A) and found that our sample is representative of citizens in Belgium for most comparable characteristics although people report poorer self-assessed health and more difficulty with monthly expenses in this survey than in national data. It is possible that the pandemic context has reduced people's health status and financial means.

[3] The study survey is available upon request to the authors.

[4] We investigated the possibility of an induced left-to-right profile order bias in the analysis due to our random color choices, blue and orange, for the left and right profiles' varying levels, but found no meaningful significant effect.

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APPENDIX A

TABLE A1 Study sample representativeness compared to the overall Belgian population

Variables	Categories	Study sample (%)	Belgian population[a] (%)
Gender	Female	51	51
	Male	49	49
Age	18–24	10	11
	25–34	17	16
	35–44	17	17
	45–54	19	18
	55–64	17	16
	65–80	20	22
Language	Dutch	57	60
	French	43	40
Province	Vlaams-Brabant	10	10
	Brabant Wallon	7	3
	Brussels Capital	9	10
	Antwerpen	15	16
	Limburg	8	8
	East Flanders	13	13
	West Flanders	10	11
	Hainaut	6	12
	Liège	10	10
	Luxembourg	5	3
	Namur	8	4
Education	None or primary school	26	34
	Secondary school	35	37
	Higher education	39	29
COVID-19 vaccine acceptance	Willing or likely to be vaccinated	74	69
	Hesitant or unlikely to be vaccinated	26	30
Difficulties with monthly expenses	Never or once a year/no or little difficulty in making ends meet	63	78
	Once every 3 months or every month/difficulty in making ends meet	37	22
Self-assessed health	Very good	14	25
	Good	41	52
	Fair	34	17
	Poor	9	5
	Very poor	1	1
	Don't know/don't want to say	1	NA

[a]Sources used: Age, gender, language, province, and education (Statbel, 2021); self-assessed health and financial situation (Sciensano, 2021); willingness to be vaccinated in September 2020 (UA, 2020).

APPENDIX B

B.1 Bayesian D-optimal partial profile design of the DCE

The design of the DCE involved three surveys of 10 choice sets with two profiles of a possible candidate for COVID-19 vaccine prioritization. The surveys appear in Table B1. Each survey was filled out by about 650 respondents. The design of 30 choice sets accounted for the independent estimation of all two-way interaction effects between the five attributes,

TABLE B1 Bayesian D-optimal partial profile design including three surveys

Survey	Choice set	Medical risk	Older than 60	Virus spreader	Cost to society (€)	Essential profession
1	1	Yes	Yes	1 other person	0	Yes
1	1	No	No	1 other person	1000	Yes
1	2	No	Yes	10 other persons	100	No
1	2	No	Yes	1 other person	1000	Yes
1	3	Yes	Yes	1 other person	0	No
1	3	No	Yes	10 other persons	1000	No
1	4	No	Yes	1 other person	100	Yes
1	4	No	No	10 other persons	100	No
1	5	No	No	1 other person	100	Yes
1	5	Yes	No	1 other person	1000	No
1	6	No	Yes	1 other person	1000	Yes
1	6	Yes	Yes	10 other persons	1000	No
1	7	Yes	No	10 other persons	1000	No
1	7	Yes	Yes	10 other persons	0	Yes
1	8	Yes	Yes	1 other person	100	Yes
1	8	Yes	No	10 other persons	0	Yes
1	9	No	Nes	1 other person	0	Yes
1	9	Yes	No	1 other person	0	No
1	10	Yes	No	1 other person	100	No
1	10	No	Yes	10 other persons	100	No
2	11	Yes	Yes	1 other person	100	No
2	11	No	No	1 other person	0	No
2	12	Yes	No	1 other person	100	Yes
2	12	Yes	No	10 other persons	0	No
2	13	Yes	No	1 other person	0	Yes
2	13	No	No	10 other persons	100	Yes
2	14	No	Yes	1 other person	0	Yes
2	14	No	No	10 other persons	0	No
2	15	Yes	No	10 other persons	100	No
2	15	No	No	10 other persons	1000	Yes
2	16	Yes	Yes	1 other person	0	Yes
2	16	No	Yes	10 other persons	0	No
2	17	No	Yes	1 other person	0	No
2	17	No	No	1 other person	100	Yes
2	18	No	No	1 other person	1000	No
2	18	No	Yes	10 other persons	0	No
2	19	No	No	10 other persons	0	Yes
2	19	Yes	Yes	10 other persons	0	No
2	20	Yes	Yes	1 other person	1000	No
2	20	No	No	10 other persons	1000	No
3	21	No	No	10 other persons	1000	No
3	21	Yes	Yes	10 other persons	100	No
3	22	No	Yes	1 other person	1000	No
3	22	No	Yes	10 other persons	0	Yes
3	23	No	No	10 other persons	0	Yes
3	23	Yes	No	1 other person	1000	Yes
3	24	Yes	No	1 other person	1000	No
3	24	Yes	Yes	10 other persons	1000	Yes
3	25	Yes	Yes	10 other persons	100	Yes
3	25	No	Yes	10 other persons	1000	No
3	26	Yes	Yes	1 other person	100	No
3	26	No	Yes	10 other persons	100	Yes
3	27	No	Yes	1 other person	100	No
3	27	No	No	1 other person	0	Yes
3	28	Yes	Yes	1 other person	1000	Yes
3	28	Yes	No	10 other persons	100	Yes
3	29	Yes	Yes	1 other person	100	Yes
3	29	No	No	1 other person	100	No
3	30	Yes	No	1 other person	1000	Yes
3	30	No	Yes	10 other persons	1000	Yes

four of which have two levels and one has three levels (i.e., the attribute "cost to society"). These attributes required the estimation of six main effects and 14 two-way interactions, which the design could accommodate.

The choice sets contained partial profiles that were described by three attributes of which the levels were varied and two attributes of which the levels were kept constant. The levels of the varying attributes were indicated in gray. The constant attributes were shown to the respondents to present actual people candidates for vaccine prioritization as well as to be able to estimate the attribute interactions. In each survey, each attribute was held constant in four choice sets and varied in six choice sets. The design was created using Kessels et al.'s (2015) partial profile design algorithm in the JMP Pro 16 software (SAS Institute Inc).

The design is Bayesian D-optimal meaning that it incorporates all available knowledge about respondents' preferences in the optimization of the determinant or D-criterion value to obtain the design that guarantees the most precise preference estimates. This was straightforward for most attributes in our DCE. That is, a person belonging to a medically vulnerable group was generally preferred for prioritization over someone who is not medically vulnerable. The same held for a heavy virus spreader, an individual with an essential profession, and an individual who had a high cost-to-society after being COVID-19 infected. We did not provide any prior preference regarding the age attribute, because this attribute could be a source of polarization or preference heterogeneity. Also, we allowed for quite some uncertainty or variability regarding all prior beliefs in the design optimization. Given this prior outlook on the preferences, the Bayesian design of Table B1 does not contain any choice sets where one candidate profile is dominating the other on every attributes. This is the strength of the Bayesian design approach (Crabbe & Vandebroek, 2012). If an older person is preferred over a younger person, then choice sets 11, 24 and 29 can be seen as choice sets with a dominant candidate. If the preference is reversed, then choice set 17 is the only choice set with a dominant candidate.

APPENDIX C

C.1 Latent class model analysis

Latent class analysis groups respondents into a prespecified number of latent classes or segments with distinct preferences. This allows for the estimation of class-specific preference parameters and of the probability of class membership (Greene & Hensher, 2003; Schreiber, 2017).

We estimated a series of latent class models with different numbers of classes using the *lclogit2* package in Stata 17 (Yoo, 2020). The goodness-of-fit-measures in terms of the log-likelihood and derived information criteria such as the popular Bayesian Information Criterion (Nylund et al., 2007) for the models with two and three latent classes were about equally optimal, but interpretability was higher for the model with two latent classes. The preference estimates of this two-class model appear in Table C1. Using this model, individuals were assigned to classes by calculating individual class probabilities for each class based on an individual's sequence of choices. The two classes showed a high correspondence with the two clusters from the post-estimation cluster analysis using the PML model, as demonstrated by the relative sizes of the model estimates, similar class or cluster shares (53% for class 1 and 47% for class 2) and a highly significant chi-square test for association between the classes and the clusters. The assumption of a multivariate normal parameter distribution underlying the PML model analysis is therefore adequate.

TABLE C1 Latent class model estimates for the sample choice data

	Class 1 ($N = 1036$)				Class 2 ($N = 908$)			
Term	**Mean**	**Standard error**	**Lower 95%**	**Upper 95%**	**Mean**	**Standard error**	**Lower 95%**	**Upper 95%**
Medical risk group								
Yes	0.172**	0.022	0.129	0.215	0.821**	0.037	0.748	0.894
No	−0.172**	0.022	−0.215	−0.129	−0.821**	0.037	−0.894	−0.748
Older than 60								
Yes	−0.145**	0.021	−0.187	−0.103	0.317**	0.023	0.271	0.363
No	0.145**	0.021	0.103	0.187	−0.317**	0.023	−0.363	−0.271

(Continues)

TABLE C1 (Continued)

Term	Class 1 ($N = 1036$) Mean	Standard error	Lower 95%	Upper 95%	Class 2 ($N = 908$) Mean	Standard error	Lower 95%	Upper 95%
Virus spreader								
10 other persons	0.481**	0.022	0.438	0.524	0.302**	0.027	0.248	0.356
1 other person	−0.481**	0.022	−0.524	−0.438	−0.302**	0.027	−0.356	−0.248
Cost to society								
0 € per day	−0.182**	0.025	−0.232	−0.132	−0.052	0.035	−0.120	0.016
100 € per day	0.003	0.024	−0.044	0.050	0.033	0.026	−0.018	0.084
1000 € per day	0.179**	0.026	0.127	0.231	0.039	0.036	−0.031	0.109
Essential profession								
Yes	0.220**	0.025	0.172	0.268	0.753**	0.029	0.697	0.809
No	−0.220**	0.025	−0.268	−0.172	−0.753**	0.029	−0.809	−0.697
Class membership constant	0.121	0.089	−0.053	0.296				
Class share	53%				47%			

** Significant at $p < 0.001$.