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. 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, 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 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.
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. 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
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 \textit{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).
| 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
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 lower than older respondents as a preferred vaccination strategy [Colour figure can be viewed at wileyonlinelibrary.com]

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]
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.
| 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.
**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 | p-Value |
|----------------------------------------------|----------|------------|---------|---------|
| 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   |
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 into 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.

REFERENCES
Bloom, B. R., Nowak, G. J., & Orenstein, W. (2020). “When will we have a vaccine?”—Understanding questions and answers about Covid-19 vaccination. *New England Journal of Medicine*, 383, 2202–2204. https://doi.org/10.1056/NEJMp2025331

Borriello, A., Master, D., Pellegrini, A., & Rose, J. M. (2021). Preferences for a COVID-19 vaccine in Australia. *Vaccine*, 39(3), 473–479. https://doi.org/10.1016/j.vaccine.2020.12.032

Bryan, S., & Dolan, P. (2004). Discrete choice experiments in health economics: For better or for worse? *The European Journal of Health Economics*, 5(3), 199–202. https://doi.org/10.1007/s10198-004-0241-6

CDC. (2020). Phased allocation of COVID-19 vaccines. Centers for Disease Control and Prevention. https://www.cdc.gov/mmwr/volumes/69/wr/mm695152e2.htm

Chernozhukov, V., Kasahara, H., & Schrimpf, P. (2021). Causal impact of masks, policies, behavior on early Covid-19 pandemic in the U.S. *Journal of Econometrics*, 220(1), 23–62. https://doi.org/10.1016/j.jeconom.2020.09.003
Crabbe, M., & Vandebroek, M. (2012). Using appropriate prior information to eliminate choice sets with a dominant alternative from D-efficient designs. *Journal of Choice Modelling*, 5(1), 22–45. https://doi.org/10.1016/S1755-5345(13)70046-0

Diederich, A., Swait, J., & Wirsik, N. (2012). Citizen participation in patient prioritization policy decisions: An empirical and experimental study on patients’ characteristics. *PloS One*, 7(5), e36824. https://doi.org/10.1371/journal.pone.0036824

Duch, R., Roope, L. S. J., Violato, M., Fuentes Becerra, M., Robinson, T., Bonnefon, J.-F., Friedman, J., Loewen, P., Mamidi, P., Melegaro, A., Blanco, M., Vargas, J., Seither, J., Candiolo, P., Gibertoni Cruz, A., Hua, X., Barnett, A., & Clarke, P. M. (2021). Who should be first in line for the COVID-19 vaccine? Surveys in 13 countries of the public’s preferences for prioritisation. *medRxiv*, 2021.01.31.21250866. https://doi.org/10.1101/2021.01.31.21250866

Emanuel, E. J., Persad, G., Kern, A., Buchanan, A., Fabre, C., Halliday, D., Heath, J., Herzog, L., Leland, R. J., Lemango, E. T., Luna, F., McCoy, M. S., Norheim, O. F., Ottersen, T., Schaefer, G. O., Tan, K. C., Wellman, C. H., Wolff, J., & Richardson, H. S. (2020). An ethical framework for global vaccine allocation. *Science*, 369(6509), 1309–1312. https://doi.org/10.1126/science.abe2803

Emanuel, E. J., Persad, G., Upshur, R., Thome, B., Parker, M., Glickman, A., Zhang, C., Boyle, C., Smith, M., & Phillips, J. P. (2020). Fair allocation of scarce medical resources in the time of Covid-19. *New England Journal of Medicine*, 382(21), 2049–2055. https://doi.org/10.1056/NEJMsb2005114

European Commission. (Ed.). (2020). *Preparedness for COVID-19 vaccination strategies and vaccine deployment*. Brussels European Commission. https://ec.europa.eu/commission/presscorner/detail/en/ip_20_1903

Florin, D., & Dixon, J. (2004). Public involvement in health care. *BMI*, 328(7432), 159–161. https://doi.org/10.1136/bmj.328.7432.159

Gayle, H., Foeg, W., Brown, L., Kahn, B., & Coronavirus Committee on Equitable Allocation of Vaccine for the Novel, Policy Board on Health Sciences, Health Board on Population, Practice Public Health Committee, Health, Division Medicine, Engineering National Academies of Sciences, and Medicine. (2020). The National Academies collection: Reports funded by National Institutes of Health. In NASEM, *Framework for equitable allocation of COVID-19 vaccine*. (pp. 1–272). National Academies Press (US), National Academy of Sciences.

Gollust, S. E., Saloner, B., Hest, R., & Blewett, L. A. (2020). US adults’ preferences for public allocation of a vaccine for coronavirus disease 2019. *JAMA Network Open*, 3(9), e2023020. https://doi.org/10.1001/jamanetworkopen.2020.23020

Goossens, L. M., Utens, C. M., Smeenk, F. W., Donkers, B., van Schayck, O. C., & Rutten-van Molken, M. P. (2014). Should I stay or should I go home? A latent class analysis of a discrete choice experiment on hospital-at-home. *Value in Health*, 17(5), 588–596. https://doi.org/10.1016/j.jval.2014.05.004

Greene, W. H., & Hensher, D. A. (2003). A latent class model for discrete choice analysis: Contrasts with mixed logit. *Transportation Research Part B: Methodological*, 37(8), 681–698. https://doi.org/10.1016/S0191-2615(02)00046-2

JCVI.(2020). *Priority groups for coronavirus (COVID-19) vaccination*: Advice from the JCVI Joint Committee on Vaccines and Immunization. https://www.gov.uk/government/publications/priority-groups-for-coronavirus-covid-19-vaccination-advice-from-the-jcvi-30-december-2020/joint-committee-on-vaccination-and-immunisation-advice-on-priority-groups-for-covid-19-vaccination-30-december-2020

Johnson, F. R., Yang, J.-C., & Reed, S. D. (2019). The internal validity of discrete choice experiment data: A testing tool for quantitative assessments. *Value in Health*, 22(2), 157–160. https://doi.org/10.1016/j.jval.2018.07.876

Jonker, M. F., Donkers, B., de Bekker-Grob, E., & Stolk, E. A. (2019). Attribute level overlap (and color coding) can reduce task complexity, improve choice consistency, and decrease the dropout rate in discrete choice experiments. *Health Economics*, 28(3), 350–363. https://doi.org/10.1002/hec.3846

Kessels, R., Jones, B., & Goos, P. (2011). Bayesian optimal designs for discrete choice experiments with partial profiles. *Journal of Choice Modelling*, 4(3), 52–74.

Kessels, R., Jones, B., & Goos, P. (2015). An improved two-stage variance balance approach for constructing partial profile designs for discrete choice experiments. *Journal of Choice Modelling*, 4(3), 52–74.

Kessels, R., Jones, B., Goos, P., & Vandebroek, M. (2011). The usefulness of Bayesian optimal designs for discrete choice experiments. *Applied Stochastic Models in Business and Industry*, 27(3), 173–188.

Liu, Y., Salwi, S., & Drolet, B. C. (2020). Multivalue ethical framework for fair global allocation of a COVID-19 vaccine. *Journal of Medical Ethics*, 46(8), 499–501. https://doi.org/10.1136/medethics-2020-106516

Louviere, J., Hensher, D., & Swait, J. (2000). *Stated choice methods: Analysis and applications*. Cambridge University Press.

Louviere, J. J. (2006). What you don’t know might hurt you: Some unresolved issues in the design and analysis of discrete choice experiments. *Environmental and Resource Economics*, 34(1), 173–188. https://doi.org/10.1007/s10640-005-4817-0

Louviere, J. J., Islam, T., Wasi, N., Street, D., & Burgess, L. (2008). Designing choice experiments: Do optimal designs come at a price? *Journal of Consumer Research*, 35(2), 360–375. https://doi.org/10.1086/586913

Luyten, J., Kessels, R., Atkins, K. E., Jit, M., & van Hoek, A. J. (2019). Quantifying the public’s view on social value judgments in vaccine decision-making: A discrete choice experiment. *Social Science & Medicine*, 228, 181–193. https://doi.org/10.1016/j.socscimed.2019.03.025

Luyten, J., Kessels, R., Goos, P., & Beutels, P. (2015). Public preferences for prioritizing preventive and curative health care interventions: A discrete choice experiment. *Value in Health*, 18(2), 224–233. https://doi.org/10.1016/j.jval.2014.12.007

Mahase, E. (2020). Covid-19: Vaccine candidate may be more than 90% effective, interim results indicate. *BMJ*, 371, m4347. https://doi.org/10.1136/bmj.m4347

Mallapaty, S., & Ledford, H. (2020). COVID-vaccine results are on the way —and scientists’ concerns are growing. *Nature*, 586(7827), 16–17. https://doi.org/10.1038/d41586-020-02706-6

Mitze, T., Kosfeld, R., Rode, J., & Walde, K. (2020). Face masks considerably reduce COVID-19 cases in Germany. *Proceedings of the National Academy of Sciences of the United States of America*, 117(51), 32293–32301. https://doi.org/10.1073/pnas.2015954117
Mouter, N., Collewet, M., de Wit, G. A., Rotteveel, A., Lambooij, M. S., & Kessels, R. (2021). Societal effects are a major factor for the uptake of the coronavirus disease 2019 (COVID-19) digital contact tracing app in The Netherlands. *Value in Health, 24*(5), 658–667. https://doi.org/10.1016/j.jval.2021.01.001

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class Analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal, 14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Persad, G., Emanuel, E. J., Sangenito, S., Glickman, A., Phillips, S., & Largent, E. A. (2021). Public perspectives on COVID-19 vaccine prioritization. *JAMA Network Open, 4*(4), e217943. https://doi.org/10.1001/jamanetworkopen.2021.7943

Ratcliffe, J., Bekker, H. L., Dolan, P., & Edlin, R. (2009). Examining the attitudes and preferences of health care decision-makers in relation to access, equity and cost-effectiveness: A discrete choice experiment. *Health Policy, 90*(1), 45–57. https://doi.org/10.1016/j.healthpol.2008.09.001

Roope, L. S. J., Buckell, J., Becker, F., Candio, P., Violato, M., Sindelar, J. L., Barnett, A., Duch, R., & Clarke, P. M. (2020). How should a safe and effective COVID-19 vaccine be allocated? Health economists need to be ready to take the baton. *PharmacoEconomics—Open, 4*, 557–561. https://doi.org/10.1007/s41669-020-00228-5

Ryan, M., Gerard, K., & Amaya-Amaya, M. (2008). *Using discrete choice experiments to value health and health care*. Springer.

Sandorf, E. D. (2019). Did you miss something? Inattentive respondents in discrete choice experiments. *Environmental and Resource Economics, 73*(4), 1197–1235. https://doi.org/10.1007/s10640-018-0296-y

Savulescu, J., Persson, I., & Wilkinson, D. (2020). Utilitarianism and the pandemic. *Bioethics, 34*(6), 620–632. https://doi.org/10.1111/bioe.12771

Schreiber, J. B. (2017). Latent class analysis: An example for reporting results. *Research in Social and Administrative Pharmacy, 13*(6), 1196–1201. https://doi.org/10.1016/j.sapharm.2016.11.011

Sciensano. (2021). *Health interview survey*. Belgian Government. https://his.wiv-isp.be/SitePages/Home.aspx

Simpson, E. H. (1951). The interpretation of interaction in contingency tables. *Journal of the Royal Statistical Society: Series B, 13*(2), 238–241.

Statbel. (2021). *Structure of the population*. Belgian Government. https://statbel.fgov.be/en/themes/population/structure-population#panel-14

Subbaraman, N. (2020). Who gets a COVID vaccine first? Access plans are taking shape. *Nature, 585*(7826), 492–493. https://doi.org/10.1038/d41586-020-02684-9

Train, K. (2009). *Discrete choice methods with simulation* (2nd ed.). Cambridge University Press.

Williams, A., & Evans, J. G. (1997). The rationing debate. Rationing health care by age. *BMJ, 314*(7083), 820. https://doi.org/10.1136/bmj.314.7083.820

World Health Organization. (2020). *WHO SAGE values framework for the allocation and prioritization of COVID-19 vaccination*. World Health Organization. https://apps.who.int/iris/handle/10665/334299

Wouters, O., Shadlen, K., Salcher-Konrad, M., Pollard, A., Larson, H., Teerawattananon, Y., & Jit, M. (2021). Challenges in ensuring global access to COVID-19 vaccines: Production, affordability, allocation, and deployment. *The Lancet, 397*(10278), 1023–1034.

Yoo, H. (2020). lclogit2: An enhanced command to fit latent class conditional logit models. *The Stata Journal, 20*(2), 405–425.

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### APPENDIX A

**TABLE A1  Study sample representativeness compared to the overall Belgian population**

| Variables       | Categories              | Study sample (%) | Belgian populationa (%) |
|-----------------|-------------------------|------------------|--------------------------|
| 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 |

*aSources 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).*
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.

| 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      | 2          | No           | No            | 1 other person | 100                 | No                  |
| 1      | 3          | No           | Yes           | 10 other persons | 0                   | Yes                 |
| 1      | 4          | No           | No            | 10 other persons | 100                 | No                  |
| 1      | 5          | Yes          | No            | 1 other person | 1000                | Yes                 |
| 1      | 6          | No           | Yes           | 1 other person | 1000                | Yes                 |
| 1      | 7          | Yes          | Yes           | 1 other person | 0                   | Yes                 |
| 1      | 8          | Yes          | Yes           | 1 other person | 100                 | Yes                 |
| 1      | 9          | No           | No            | 1 other person | 0                   | No                  |
| 1      | 10         | Yes         | No            | 1 other person | 100                 | No                  |
| 1      | 11         | No           | Yes           | 1 other person | 0                   | No                  |
| 1      | 12         | Yes          | No            | 1 other person | 100                 | Yes                 |
| 1      | 13         | Yes          | No            | 1 other person | 0                   | Yes                 |
| 1      | 14         | No           | Yes           | 1 other person | 0                   | Yes                 |
| 1      | 15         | No           | No            | 10 other persons | 1000                | No                  |
| 1      | 16         | Yes          | Yes           | 1 other person | 0                   | Yes                 |
| 1      | 17         | No           | Yes           | 10 other persons | 0                   | No                  |
| 1      | 18         | Yes          | No            | 1 other person | 1000                | No                  |
| 1      | 19         | No           | Yes           | 10 other persons | 0                   | No                  |
| 1      | 20         | Yes          | Yes           | 1 other person | 1000                | No                  |
| 1      | 21         | No           | No            | 10 other persons | 1000                | No                  |
| 1      | 22         | Yes          | Yes           | 10 other persons | 100                 | No                  |
| 1      | 23         | No           | Yes           | 1 other person | 1000                | No                  |
| 1      | 24         | Yes          | No            | 1 other person | 1000                | Yes                 |
| 1      | 25         | Yes          | Yes           | 10 other persons | 1000                | Yes                 |
| 1      | 26         | Yes          | Yes           | 10 other persons | 100                 | No                  |
| 1      | 27         | No           | Yes           | 1 other person | 100                 | Yes                 |
| 1      | 28         | Yes          | Yes           | 1 other person | 1000                | Yes                 |
| 1      | 29         | Yes          | Yes           | 1 other person | 100                 | Yes                 |
| 1      | 30         | Yes          | No            | 1 other person | 1000                | Yes                 |

**Table B1** Bayesian D-optimal partial profile design including three surveys.
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.

| Term                        | Class 1 (N = 1036) | Class 2 (N = 908) |
|-----------------------------|--------------------|-------------------|
|                             | 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)
| Term                          | Class 1 ($N = 1036$) | Class 2 ($N = 908$) |
|------------------------------|----------------------|---------------------|
|                              | Mean | Standard error | Lower 95% | Upper 95% | 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 $p < 0.001$. 