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# Who should get the scarce ICU bed? The US public's view on triage in the time of COVID-19

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## ABSTRACT

**Objective** To determine the relative importance members of the US public place on different patient attributes in triage decisions about who should receive the last available intensive care unit (ICU) bed.

**Methods** A discrete choice experiment was conducted with a nationally representative sample of 2000 respondents from the YouGov internet panel of US households. Respondents chose which of three hypothetical patients with COVID-19 should receive an ICU bed if only one were available. The three patients differed in age, gender, Alzheimer's-like disability and probability of survival if the patient received the ICU bed. An experimental design varied the values of the four attributes of the three hypothetical patients with COVID-19 that a respondent saw in four choice tasks.

**Results** The most important patient attribute to respondents was the probability the patient survives COVID-19 if they get the ICU bed (OR CI: 4.41 to 6.91). There was heterogeneity among different age groups of respondents about how much age of the patient mattered. Respondents under 30 years of age were more likely to choose young patients and old patients, and less likely to select patients aged 40–60 years old. For respondents in the age group 30–49 years old, as the age of the patient declined, their preference for saving the patient declined modestly in a linear fashion.

**Conclusions** Respondents favoured giving the last ICU bed available to the patient with the highest probability of surviving COVID-19. Public opinion suggests a simple guideline for physician choices based on likelihood of survival as opposed to the number of life-years saved. There was heterogeneity among respondents of different age groups for allocating the last ICU bed, as well as to the importance of the patient having an Alzheimer's-like disability (where religion of the respondent is important) and the gender of the patient (where the gender and racial identity are important).

## INTRODUCTION

The COVID-19 pandemic has forced doctors in many locations around the world to face the difficult triage question of who should get the last intensive care unit (ICU) bed when the demand for facilities exceeds supply. The question of how to allocate scarce health resources has been discussed in the literature, for natural disasters and healthcare emergencies,<sup>1–4</sup> and specifically for COVID-19.<sup>5–9</sup> This literature on triage choices is largely focused on the ethical principles that should be used, with some consideration to what is practical in an emergency situation in which health professionals have

## Key messages

### What is already known on this subject

- Current guidance on triage choices is largely focused on the ethical principles that should be used, with some consideration to what is practical in an emergency situation in which health professionals have little time to deliberate.

### What this study adds

- The US public do not support triage policies that would put less weight on saving the lives of older adults.
- Physicians in emergency settings such as the COVID-19 pandemic can make rapid judgements based on a simple heuristic of 'what patient has the highest probability to survive if they get the ICU bed,' without having to consider a host of other ethical considerations.

little time to deliberate. For example, Emanuel *et al*<sup>5</sup> put forth a number of recommendations for triage choices. Among these, they advise physicians to concentrate on the number of lives saved, but also propose the alternative metric of the number of life-years saved (recommendation 1). But they also note: 'Limited time and information in a COVID-19 pandemic ... counsel against incorporating patients' future quality of life, and quality-adjusted life-years, into benefit maximization.'

In addition to the limited time available for decision-making, what distinguishes triage decisions in the COVID-19 pandemic is the fact that the probability of death due to COVID-19 is much higher among elderly patients.<sup>10</sup> However, age is not perfectly correlated with survival probability<sup>11</sup>; pre-existing health conditions and disabilities are also associated with higher mortality risk.<sup>12</sup> At least one US political leader has indicated a willingness to sacrifice elderly patients and those with Alzheimer's in order to open up the economy and prevent business losses.<sup>13</sup> Although this argument is in opposition to the ethical recommendations put forward by health and other experts, it continues to receive considerable national and international attention and public support.<sup>14</sup>

We wished to determine how the American public would like such triage decisions to be made, that is, what choices would members of the American public make if they were put in the shoes of



an ED physician who is forced to choose which patient with COVID-19 should get the last available ICU bed. Such evidence on public opinion is important for two reasons. First, a public health policy that aligns with the public's preferences is likely to face less resistance and be easier to implement. Knowing whether any particular plan is congruent or divergent from the public's view is critical information for developing communication strategies that effectively convey the rationale for the policy adopted and in understanding objections that might be raised. Second, a public health policy on how to manage ICU triage that has the support of the public has more claim to legitimacy than a policy designed solely by experts.

In a large nationally representative survey, we asked respondents to choose which of three hypothetical patients with COVID-19 should receive an ICU bed if only one bed was available. The analysis of these survey data enables us to determine if the US public's preferences are consistent with Emanuel *et al*'s main triage recommendation.

## METHODS

We used a discrete choice experiment<sup>15</sup> to analyse the data collected from 2000 respondents from the YouGov internet panel of US households. In the survey research community, a sample size of 500 respondents is considered adequate to represent the views on the US population on standard survey questions (eg, a sample size of 500 translates into a 95% CI of  $\pm 4.3\%$  for a true split of 50/50 in the population on a favour/oppose type question). A random sample of 2000 Americans is considerably larger than used in most academic and policy relevant studies, and ensured that our sample would not be underpowered.

YouGov maintains an online panel of several million respondents who answer their clients' surveys. For our survey, YouGov drew a random sample of their respondents that matched the demographic characteristics of the US population. The sample of 2000 respondents from the YouGov panel used in this study closely matches the 2019 census population averages for key socioeconomic and demographic characteristics (see online supplemental table S1).

Respondents were interviewed between 28 August and 4 September 2020. The questionnaire provided respondents with a simple explanation of what survival probability means and then presented respondents with four 'choice tasks' in which they had to choose which of three hypothetical patients with COVID-19

(based on combination of attributes) should receive an ICU bed if only one bed was available. The ICU bed is described as having both oxygen and ventilator available. Respondents were told that all three patients were 'almost certain' to die without an ICU bed. The three patients differed in four ways: (a) age, (b) gender, (c) the presence or absence of an Alzheimer's-like disability and (d) the patient's probability of survival if they received the ICU bed. The sampling methodology and survey administration are described in the online supplemental materials (see S1 YouGov Sampling Methodology and S2 IRB Approval and Survey Administration).

Age was the key patient attribute used to distinguish a respondent's preferences between saving a patient's life now and saving a patient with the most life-years remaining. We included the patient's gender and mental disability because our pretest results suggested that these attributes were important for some respondents. In order to clearly distinguish the mental disability attribute from the probability of survival, we described it as 'Alzheimer's or a similar mental disability that makes it impossible for the person regardless of their age to take care of themselves.'

Table 1 presents an example of the table respondents saw for one of the four choice tasks they received. The values of the four attributes for patients A and B were randomly assigned using an experimental design described in the online supplemental materials (see S3 Experimental Design). For age, the levels are 20, 40, 60 and 80 years old. For gender, female and male; and for having an Alzheimer's-like mental disability, the two levels are yes and no. For survival probability, the levels are 20%, 40%, 60% and 80%. The values for the four attributes for patient C were fixed and the same for all four choice tasks and for all respondents (50 years old, female, not having an Alzheimer's-like mental disability and having a survival probability of 50% if they received the ICU bed) (see S4 for data results that show the effectiveness of the randomisation process).

The four discrete choice tasks that each respondent answered can be conceptualised as a generalisation of a simple dose-response experiment in which there are only two patients and the patient characteristics are identical except for one variable such as survival probability. In a simple dose-response experiment, this single variable is randomly varied for patient B and the response (picking patient B or not) is observed. Our

**Table 1** Example of respondent choice task

### Allocating ICU beds during a shortage

Without access to an ICU with oxygen and a medical device called a ventilator that helps someone breathe, some patients infected with COVID-19 are almost certain to die. Because of a spike in many severely ill patients with COVID-19, a hospital may face a situation where it has three patients who need a bed in an ICU unit but only one ICU bed is available. This table shows the characteristics of the three patients with respect to age and gender, as well as whether they have Alzheimer's or a similar mental disability that makes it impossible for the person regardless of their age to take care of themselves.

The last row provides information on how likely it is for the patient to survive if they get access to room in the ICU with oxygen and a ventilator. 50% indicates half of the time the patient who gets access to the ICU will survive and be able to breathe normally again and half of the time the patient will end up dying. 60% indicates that 6 out of 10 patients with characteristics similar to this one will end up living if they get a room in the ICU and other 4 will end up dying, while 40% indicates that 4 out of 10 patients similar to this one who get a room in the ICU will end up living and 6 will end up dying.

	Patient A	Patient B	Patient C
Age	60	20	50
Gender	Female	Male	Female
Has Alzheimer's or similar mental disability	Yes	No	No
Chance of survival if gets ICU bed	80%	40%	50%

If only one unused ICU bed is available at the hospital, which patient do you think the emergency room doctor should give it to?

Patient A ☐ Patient B ☐ Patient C ☐

ICU, intensive care unit.

experimental design allows multiple characteristics to be simultaneously varied and the use of three rather than two hypothetical patients and four choice sets greatly increases statistical power. The decisions respondents make reveal their trade-offs between the attributes of the patients.

Based on random utility theory,<sup>15 16</sup> we used a conditional logit model to explain the choices that respondents made regarding which of the three hypothetical patients should receive the remaining ICU bed (see S5 Random Utility Models in the online supplemental materials). Including the option of patient C (whose attribute levels were fixed) in the respondents' choice sets ensured statistical identification (because it allowed a common comparison) and increased statistical efficiency in the centre of the ranges of values that respondents saw for the attributes age and survival probability. If most respondents tend to pick the youngest patient for the ICU bed, the coefficient on age would be negative (as the age of a patient increases, the probability of choosing that patient declines). If most respondents tend to avoid giving the ICU bed to the patient with an Alzheimer's-like mental disability, the coefficient on that variable would be negative (because the probability of choosing a patient with a mental disability is less than of choosing a patient without a mental disability). Since we are using a logit model, the parameters can easily be expressed in OR form.

### Patient and public involvement

Neither the respondents nor the public were involved in the development of the research questions or outcome measures, nor informed by their priorities, experience, and preferences. However, the objective of the research was to determine respondents' preferences and priorities. No patients were involved in this study.

### RESULTS

The model results presented in table 2 show that the most important patient attribute (OR CI: 4.41 to 6.91) in determining which of the three hypothetical patients most respondents chose to receive the last ICU bed is the probability the patient survives COVID-19 if they get the ICU bed.

The results in table 2 also show that on average our respondents have a slight preference for female patients receiving the ICU bed (OR CI: 1.16 to 1.28) and against patients with an Alzheimer's-like mental disability (OR CI: 0.74 to 0.83). The average respondent would be indifferent between allocating the remaining ICU bed to a male patient and a female patient with 10% smaller survival probability than the male patient. The average respondent would be

indifferent between allocating the remaining ICU bed to a patient without a mental disability and a patient with an Alzheimer's-like mental disability and a 14% higher survival probability than the patient without an Alzheimer's-like mental disability. Respondents do not favour giving the last ICU bed to younger patients (ie, they do not prioritise saving the most life-years); indeed, the OR of the age attribute is greater not less than one (OR CI: 1.000 to 1.004). The ORs for how the four patient attributes affect respondents' choices are shown in figure 1.

Our results summarize on average the opinions of members of the US public about who should receive the scarce ICU bed, but mask considerable underlying preference heterogeneity. Figure 2 shows how the age of the patient affects the probability that the patient is chosen to receive the remaining ICU bed for four different age groups of respondents (<30 years, 30–49 years, 50–69 years, >70 years). The age variable on the x-axis in figure 2 shows the attribute of the patient that respondents saw in the choice experiment. The age groups in figure 2 represented by the blue, red, green and purple lines classify the respondents' answers to the choice experiment by the respondent's age. Respondents under 30 years of age were more likely (other things equal) to choose young patients and old patients, and less likely to select patients aged 40–60 years old. The preferences of respondents in the age group 30–49 years old were different; their choices revealed that as the age of the patient declined, their preference for saving the patient declined modestly in a linear fashion. The choices made by respondents in the two oldest age groups (50–69 years old and >70 years old) revealed that they had very different preferences from both the youngest age group (<30 years old) and the middle-age group 30–49 years old. The two older age groups (50–69 and ≥70 years old) preferred to allocate the ICU bed to patients in the age groups 30–49 and 50–69 years old, not to the young or the old.

The error bars in figure 2 show 95% CIs for the estimates of respondents' preferences for patient age by age of respondent. Respondents' preferences over patients' age (when holding all the other attributes constant) are not statistically different for each level of the attribute of patient's age for respondents less than 30 and between 30 and 49 years, or between the groups of 50–69 years and more than 70 years. However, the preferences of respondents less than 50 years are statistically different from respondents over 50 years of age. These differences are also more pronounced when comparing preferences over young patients and middle-aged patients.

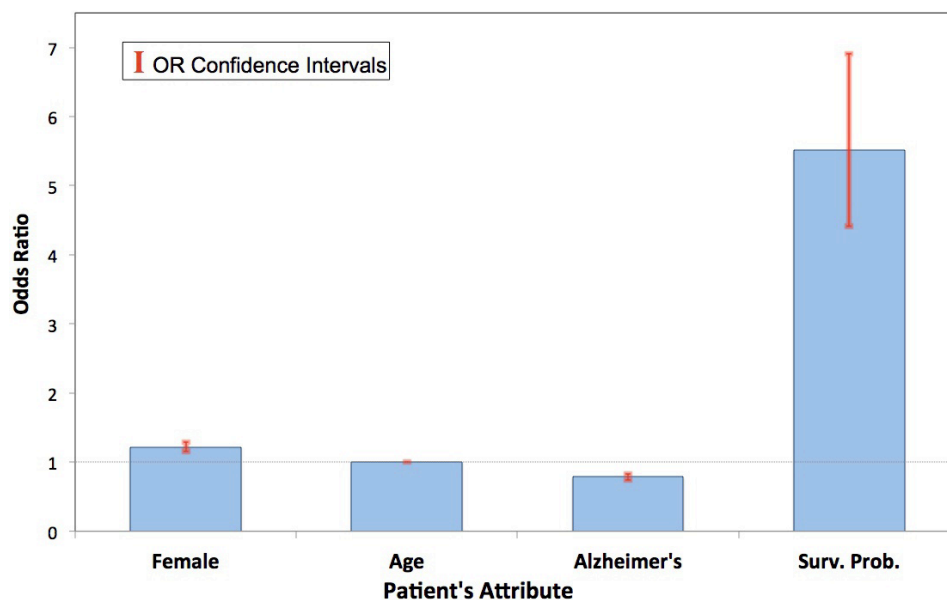
These heterogeneous preferences were also shown for race: African Americans and Hispanics put less weight on survival

**Table 2** Conditional logit model results

	OR	Robust SE	z	P> z	95% CI
Female	1.217	0.032	7.440	0.000	1.156 to 1.282
Age	1.002	0.001	2.190	0.028	1.000 to 1.004
Alzheimer's	0.785	0.023	−8.210	0.000	0.741 to 0.832
Survival probability	5.521	0.630	14.970	0.000	4.414 to 6.905
Alternative 'A' constant	1.065	0.042	1.610	0.108	0.986 to 1.151
Alternative 'B' constant	1.134	0.043	3.300	0.001	1.052 to 1.222
Alternative 'C' constant	(Base alternative)				
Log pseudo-likelihood	−8382.447				
Wald $\chi^2(4)$	283.54				
Prob> $\chi^2$	0.000				

SE adjusted for 2000 clusters in respondent number.

The use of a common option C across choice sets requires the use of alternative specific constants induced by the experimental design.

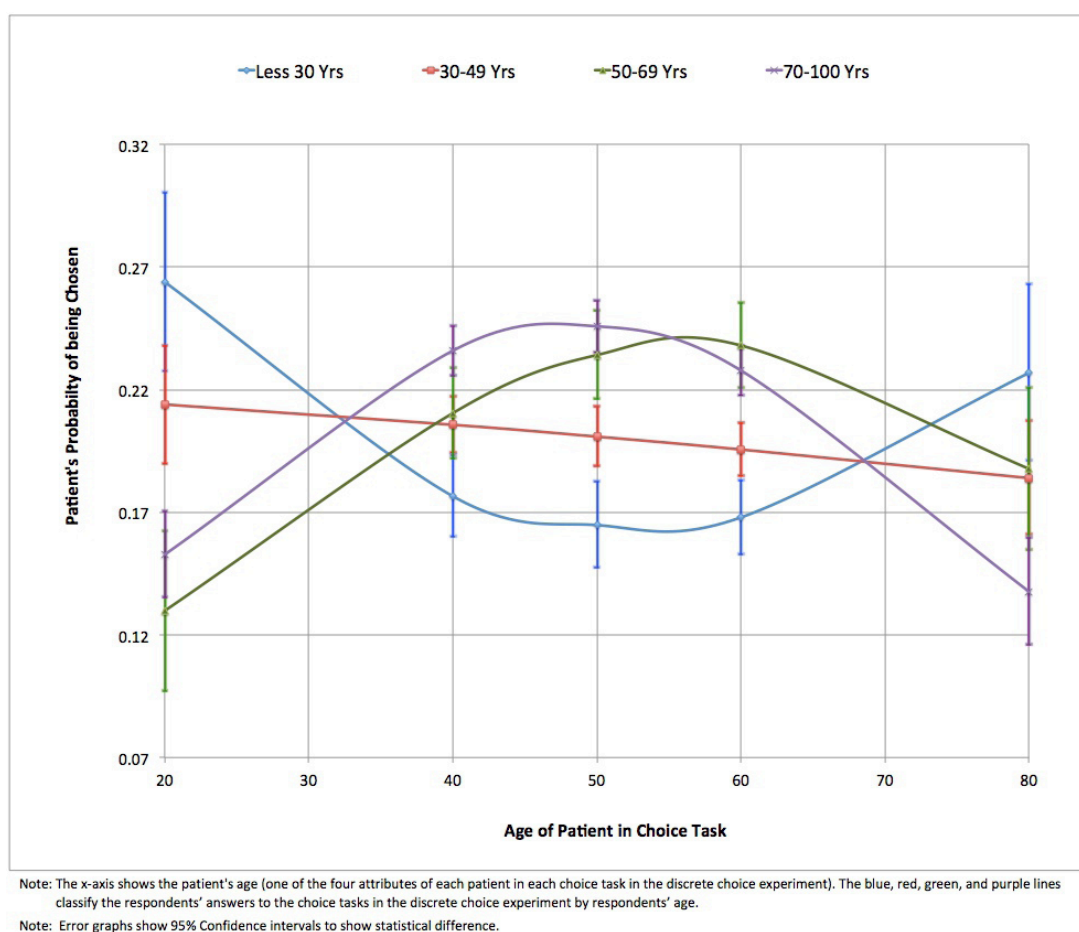


**Figure 1** ORs for patient attributes: results from conditional logit model.

probabilities than white respondents (OR CI: 0.201 to 0.481,  $p=0.000$ ). White respondents, especially those who are retired, are less likely to give the ICU bed to a patient with an Alzheimer's-like disability (OR CI: 0.556 to 0.712,  $p=0.000$ ) (see online supplemental table S7).

## DISCUSSION

Health economists have long advocated for evaluating health outcomes in terms of the value of life-years saved, thus putting more weight on saving younger individuals.<sup>17 18</sup> At the beginning



**Figure 2** Probability of choosing a patient as a function of the patient's age (for four different age groups of respondents).



of the COVID-19 epidemic, the lieutenant governor of Texas, Dan Patrick, said that grandparents were willing to sacrifice themselves in order to keep the economy from shutting down.<sup>13</sup> Our study suggests that the US public do not support triage policies that would put less weight on saving the lives of older adults.

The setting for our study is a hospital facing a spike in critically ill patients with COVID-19. We asked a national representative sample of the American public what types of patients should receive priority for a limited supply of ICU beds. Their answers reveal what they would like physicians to do in such a triage situation. Our results suggest that physicians in emergency settings such as the COVID-19 pandemic can make rapid judgements based on a simple heuristic of 'what patient has the highest probability to survive if they get the ICU bed,' without having to consider a host of other ethical considerations. In other words, the public preferences captured through our choice experiment and modelled with a conditional logit model support Emanuel *et al*'s<sup>5</sup> recommendation that physicians should focus on maximising lives saved (the survival probability attribute in our discrete choice experiment), but not worry about saving the most life-years. From our perspective, the much smaller magnitude of the effects of age, gender and mental disability suggests these attributes are not relevant to practical triage policy.

Grover *et al*<sup>19</sup> have also recently evaluated public preferences for scarce medical resources in the context of the current COVID-19 pandemic using a method that ranks eight ethical positions with respect to the allocation of scarce resources. They found the highest rank for 'saving the most lives,' followed by 'sickest first', and then in a third and less preferred place for 'youngest first'. However, their ranking method does not enable them to identify the trade-offs respondents would make between patient attributes, which our approach does by asking survey respondents to make an explicit choice between patients with different attributes.

Our results do indicate that respondents' preferences are complex and heterogeneous, especially with respect to the priority given by different respondents to the age of the patient. This complex age effect is largely driven by middle-aged respondents exhibiting a stronger preference for saving middle-aged patients. All the casual talk by some political commentators that old folks in nursing homes, who are at high risk of COVID-19 infection and mortality, are a drain on the economy, and should be jettisoned first, is inconsistent with what the majority of the American public want. Further, our respondents had little proclivity to sacrifice someone with an Alzheimer's-like mental disability if their probability of survival is noticeably higher than another patient who needs the scarce ICU bed. We expect that even this modest adverse selection factor would be considerably smaller for the vast majority of other disabilities a physician might encounter in a triage situation.

In summary, in an overwhelmed hospital situation, the US public favour a simple triage decision rule: if physicians have to choose how to allocate a scarce ICU hospital bed, pick the patient with the best chance of making it. Of course, following public preferences is not the only way to determine who should receive an ICU bed. Clearly, healthcare professionals may have different opinions, given their experience. Policies based on public preferences are not a priori the optimal approach to select patients for an ICU bed. However, whether public preferences are convergent or divergent from those of healthcare professionals, knowledge of them should be useful in developing effective communication strategies by doctors and hospitals. We make no claim that these findings would apply in countries outside the USA.

## Limitations

In most surveys in which respondents are asked to make decisions that relate to risks that change survival probabilities, the changes in survival probabilities are quite small and can be hard for many individuals to understand. Also, respondents are often presented with choice situations that are hard to understand and have little policy relevance. Our situation is quite different. Our respondents are asked questions about changes in survival probabilities that were large; where the choice context was easily understandable due to media reports on the COVID-19 pandemic; and where the relevance of public input to the policy process was clear.

Nevertheless, there are three main limitations of our study. First, like the vast majority of doctors, our respondents have never been put in a situation where they would actually need to make choices similar to those posed in the survey. Thus, they have no prior experience making this type of decision. If a sample of participants with prior experience was desired, one would need to turn to medical personnel with experience in active war or disaster zones. As noted in the introduction, our research findings should not be seen as a substitute for informed medical judgement but rather as an input to a broader process for drafting guidance for handling triage decisions in epidemics or large-scale disasters where the choices might be similar to the situation we described to respondents.

Second, we provided our respondents with a relatively short list of patient attributes: age, gender, major disability and survival probabilities. We could have presented respondents with choices in which the hypothetical patients had more attributes. For instance, other attributes might be the nature of the medical problems that the patient faces after time spent in the ICU. Additional patient attributes could be added to our existing survey instrument, but we think researchers should be careful not to add attributes that concern problems about which people expect doctors to make expert judgements.

Third, our research only looks at the COVID-19 context. While a reasonable assumption would be that that our work is applicable to other contexts, such as earthquakes, tropical cyclones or pandemics that involved diseases with characteristics substantively different than that of a respiratory virus, it would be useful to establish this with empirical work.

**Contributors** MH, RTC and DW conceptualised the research and designed the survey instrument. JJJ and RTC prepared the experimental design. RTC and HCC conducted the data analysis. All authors participated in the interpretation of the results and drafting the manuscript. DW is the guarantor of the manuscript.

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**Patient consent for publication** Not required.

**Ethics approval** This study involves human participants. The Institutional Review Board of Arizona State University determined that the protocol for this research (IRB ID: STUDY00011907) is considered exempt pursuant to Federal Regulations 45CFR46 on May 4, 2020. Participants gave informed consent to participate in the study before taking part.

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## **Who Should Get the Scarce ICU Bed? The US Public's View on Triage in the Time of COVID-19**

### **Supplementary Materials**

- S1. You.Gov Sampling Methodology**
- S2. IRB Approval and Survey Administration**
- S3. Experimental Design**
- S4. Distribution of Respondents' Characteristics by Treatment Groups and Entire Sample**
- S5. Random Utility Models**
- S6. Probability Estimations: Preference Results over Patient Age by Respondent Age**
- S7. Results of the Model with Interacted Covariates**

### **S1. YOU.GOV Sampling Methodology**

YouGov interviewed 2,182 respondents who were then matched down to a sample of 2,000 to produce the final dataset. The respondents were matched to a sampling frame on gender, age, race, and education. The frame was constructed by stratified sampling from the full 2018 American Community Survey (ACS) 1-year sample with selection within strata by weighted sampling with replacements (using the person weights on the public use file). The matched cases were weighted to the sampling frame using propensity scores. The matched cases and the frame were combined, and a logistic regression was estimated for inclusion in the frame. The propensity score function included age, gender, race/ethnicity, years of education, and region. The propensity scores were grouped into deciles of the estimated propensity score in the frame and post-stratified according to these deciles.

**Table S1 – Characteristics of You.Gov Survey Respondents vs. US Population**

Characteristic of Respondent		You.Gov Sample	US Population (2019 ACS Census Data)
Household Size (mean)		2.8	2.6
Household Annual Income (median, US\$)		65,000	62,843
Female		53.1%	50.8%
Percent of Respondents 65 years and over (from all adults 18 years and older)		20.45%	20.51%
White		68.95%	76.3%
Black		9.75%	13.4%
Bachelor's degree or higher (percent of persons age 25 years+)		34.4%	32.1%
Age (percent of persons age 18 years+)	< 30 yrs	19.2%	20.8%
	30 – 49 yrs	32.1%	33.2%
	50 – 69 yrs	35.8%	31.7%
	> 70 yrs	13.0%	14.2%

**S2. IRB Approval and Survey Administration**

The data collection plan for this study was approved by the Arizona State University Institutional Review Board (Study 00011907). Our survey instrument was administered between August 28 and September 4, 2020 to a nationally representative sample of 2000 Americans, at least 18-years old, drawn from YouGov's U.S. internet panel of two million participants. YouGov is a leading international survey research firm (YouGov.com) which routinely does surveys for major news organizations (including CBS News and the Economist, commercial firms, government agencies, NGOs, and universities).

**S3. Experimental Design**

Discrete Choice Experiments (DCE) are based on the idea that any set of choice options that individuals choose among can be decomposed into a set of factors (often called "attributes" or "characteristics") where each factor has associated levels that can be discrete like a patient's gender or continuous like a patient's age. While it is possible to sample (or choose specific) levels for a continuous variable over some pre-defined range from a distribution like the uniform, typical practice is to use a small number of discrete levels to represent the continuous variable.

To create the options that survey respondents see in each choice set, an experimental design typically is used to assign combinations of levels of the factors of interest. The objective



of an experimental design is to adequately span the space represented by the different factors and their levels in such a way as to ensure the statistical identification of the parameters of interest and to be able to estimate them with reasonable efficiency [1, 10]. In this case we have two four-level factors and two two-level factors. All possible combinations of these attribute levels produce  $2^2 \times 4^2 = 64$  total combinations. This is known as a “Full” (or “Complete”) factorial design. The 64 combinations are infeasible to implement in survey even as large as ours due to the large number of overall questions that need to be asked. To reduce the number of possible options to a manageable number, typically a fractional factorial design is used to make a smaller set of combinations. This trades off increased reliability via more replications of the same combination of factor levels versus the ability to estimate more statistically complex models (i.e., an ability to estimate all or some higher order terms apart from only the main effects). In this case, we used an orthogonal fractional factorial design selected from the  $4^5$  Full factorial to make 16 pairs of choice options.

The procedure we used to make the combinations was to reverse code two of the four-level columns (i.e., 0=3, 1=2, 2=1, 3=0), and expand one other 4-level column into a  $2 \times 2$  factorial (0= 0 0; 1= 0 1; 2 = 1 0; 3 = 1 1). This creates one set of 16 attribute level combinations that we will term “Option A”. We then reverse coded one of the two-level columns (0 = 1; 1 =0); and used the two remaining four-level columns with the two two-level columns previously created (not reverse coded) to make a different set of 16 attribute level combinations that we will call “Option B”. Finally, we paired the 16 Option A combinations with the 16 Option B combinations randomly and without replacement to make 16 different sets of pairs. We then added the constant Option C described in Figure 1 to each pair to make a set of 16 triples. This constant option ensures statistical identification [10]. The use of a common Option C across choice sets requires the use of alternative specific constants induced by the experimental design. Here the effects for the A and B Option Indicators should be of the same sign and equal in magnitude. The coefficient estimates of Female and Alzheimer suggest a small positive effect, which cannot be rejected at the  $p < 0.05$  level. Because Options A and B are “Generic” (i.e., differentiated only by their attributes and levels, not names, labels or brands) we expect the attribute effects to be “Generic”; i.e., the same for both Options A and B, except for random statistical variation. Finally, we randomly assigned 4 triples without replacement to one of four versions to minimize task difficulty and/or the number of questions in the overall survey. This is reflected in the task shown in Figure 1, where individuals choose the patient (Option A, B, or C) who should get the only available ICU bed.

#### **S4. Distribution of Respondents’ Characteristics by Treatment Groups and Entire Sample**

The following table shows the effectiveness of the randomization process. It presents the frequency and percentage of respondents for each treatment of the choice experiment, as well as the frequency and percentage of respondents for the entire surveyed sample. Treatment groups and the entire sample have similar distributions of the respondents’ characteristics, including age categories and gender.

**Table S4: Frequency and Percentage of Respondents for Each Choice Treatment and for the Entire Sample for Gender, Age, Education and Political Party**

Choice Treatment: Experimental Design	Gender		Age				Education						Political Party			
	Female	Male	<30 yrs	30 - 49 yrs	50 - 69 yrs	>70 yrs	No HS	High scho	Some coll	2-year	4-year	Post-grad	Democrat	Republica	Independe	Other/ Unsure
<b>Treatment 1</b>	768	693	315	453	492	201	72	474	315	132	312	156	489	390	402	180
(Percent from Sample)	53	47	22	31	34	14	5	32	22	9	21	11	33	27	28	12
<b>Treatment 2</b>	825	687	273	459	582	198	84	402	348	150	357	171	567	360	396	189
(Percent from Sample)	55	45	18	30	38	13	6	27	23	10	24	11	38	24	26	13
<b>Treatment 3</b>	789	759	288	519	561	180	66	489	345	174	309	165	576	372	408	192
(Percent from Sample)	51	49	19	34	36	12	4	32	22	11	20	11	37	24	26	12
<b>Treatment 4</b>	804	675	273	495	513	198	75	444	348	144	288	180	510	423	417	129
(Percent from Sample)	54	46	18	33	35	13	5	30	24	10	19	12	34	29	28	9
<b>All Sample</b>	3,186	2,814	1,149	1,926	2,148	777	297	1,809	1,356	600	1,266	672	2,142	1,545	1,623	690
(Percent from Sample)	53	47	19	32	36	13	5	30	23	10	21	11	36	26	27	12

## S5. Random Utility Models

Random Utility Theory [1; 2] assumes that individuals have a systematic and random component associated with their preferences (or “utility”). Typically, the systematic component is assumed to be a fixed (mean) parameter, often represented as a linear function of a set of attributes, (each with its own preference parameter) characterizing the choice option. The random component is distributed according to some distribution, typically, a normal or double exponential. The latter assumption leads to the well-known Multinomial Logit Choice Model we report in this paper. More complex models are possible by making different assumptions about the systematic and random components, but they are more useful for understanding individual differences in preference or when the choice options can be naturally grouped into subsets like fast food and fine dining restaurants. The standard multinomial (conditional) logit model we use in this paper is known to be fairly robust with respect to summarizing average preferences [3].

DCEs are widely used in health economics, public health, smoking cessation and many other areas of health applications. We also note that variations of the DCE approach proposed by Louviere and Woodworth (1983) [4] are known as Best-Worst Scaling, and account for many other applications in health-related areas [5, 6, 7, 8, 9]. So, our use of DCEs in this paper follows a long tradition of inquiry and applications in medicine and health-related areas.

## S6. Probability Estimations: Preference Results over Patient Age by Respondent Age

**Table S6: Statistical Results of Probability Estimations of Each Level of the Attribute of Patient's Age (for four different age groups of respondents)**

Age: Patient Attribute	Respondents' Age Less than 30 Yrs					
	Estimated Probability	Std. Err.	z	P>z	[95% Conf. Interval]	
20	0.2638587	0.0185004	14.26	0.000	0.2275986	0.3001188
40	0.1765734	0.008431	20.94	0.000	0.1600491	0.1930978
50	0.1647865	0.0089307	18.45	0.000	0.1472827	0.1822904
60	0.1679053	0.0077499	21.67	0.000	0.1527157	0.1830949
80	0.226876	0.0183813	12.34	0.000	0.1908494	0.2629027
	Respondents' Age 30-49 Yrs					
	Estimated Probability	Std. Err.	z	P>z	[95% Conf. Interval]	
20	0.2139075	0.0123081	17.38	0.000	0.189784	0.2380311
40	0.2056855	0.0057558	35.74	0.000	0.1944042	0.2169667
50	0.2008565	0.0062312	32.23	0.000	0.1886436	0.2130693
60	0.1955977	0.0054534	35.87	0.000	0.1849092	0.2062861
80	0.1839528	0.0117994	15.59	0.000	0.1608265	0.2070791
	Respondents' Age 50-69 Yrs					
	Estimated Probability	Std. Err.	z	P>z	[95% Conf. Interval]	
20	0.1296767	0.0089484	14.49	0.000	0.1121381	0.1472152
40	0.2104233	0.0052192	40.32	0.000	0.2001939	0.2206528
50	0.2341298	0.0054072	43.3	0.000	0.223532	0.2447277
60	0.2380405	0.0051562	46.17	0.000	0.2279346	0.2481464
80	0.1877296	0.0111007	16.91	0.000	0.1659727	0.2094865
	Respondents' Age More than 70 Yrs					
	Estimated Probability	Std. Err.	z	P>z	[95% Conf. Interval]	
20	0.1527401	0.0166424	9.18	0.000	0.1201216	0.1853587
40	0.2358892	0.009456	24.95	0.000	0.2173559	0.2544226
50	0.2458452	0.0091506	26.87	0.000	0.2279103	0.2637802
60	0.2278591	0.0088114	25.86	0.000	0.210589	0.2451291
80	0.1376663	0.0169126	8.14	0.000	0.1045183	0.1708144

## S7. Results of the Model with Interacted Covariates

**Table S7: Results of Model with Interacted Covariates (Conditional Logit Model)**

	Odds Ratio		Robust Std. Err.	z	P>  z	[95% Conf. Interval]	
Biden & Female							
	0	1.054	0.037	1.530	0.126	0.985	1.128
	1	1.332	0.050	7.680	0.000	1.238	1.433
Surv. Prob.		8.927	1.043	18.730	0.000	7.100	11.226
Black or Hispanic & Survival Prob.							
	1	0.311	0.069	-5.240	0.000	0.201	0.481
Alzheimers		1.010	0.047	0.210	0.835	0.922	1.105
White & Alzheimers							
	1	0.629	0.040	-7.350	0.000	0.556	0.712
Respondents' Age Categories & Patient Age							
	18-30 yrs (respondent)	0.979	0.011	-1.940	0.052	0.959	1.000
	31-40 yrs (respondent)	0.993	0.011	-0.650	0.513	0.970	1.015
	41-50 yrs (respondent)	1.056	0.013	4.490	0.000	1.031	1.081
	51-60 yrs (respondent)	1.082	0.012	7.230	0.000	1.059	1.106
	61-70 yrs (respondent)	1.095	0.012	8.290	0.000	1.072	1.119
	>70 yrs (respondent)	1.125	0.014	9.480	0.000	1.098	1.153
Respondents' Age Categories & Squared Patient Age							
	18-30 yrs (respondent)	1.000	0.000	1.680	0.094	1.000	1.000
	31-40 yrs (respondent)	1.000	0.000	0.460	0.648	1.000	1.000
	41-50 yrs (respondent)	0.999	0.000	-4.630	0.000	0.999	1.000
	51-60 yrs (respondent)	0.999	0.000	-6.930	0.000	0.999	0.999
	61-70 yrs (respondent)	0.999	0.000	-7.890	0.000	0.999	0.999
	>70 yrs (respondent)	0.999	0.000	-9.780	0.000	0.999	0.999
Alternative 'A' constant							
		1.280	0.052	6.130	0.000	1.183	1.385
Alternative 'B' constant		1.371	0.055	7.900	0.000	1.268	1.482
Alternative 'C' constant				(Base alternative)			

Std. Err. adjusted for 2,000 clusters in respondent\_number.

The use of a common Option C across choice sets requires the use of alternative specific constants induced by the experimental design.

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**¿Quién Debería Recibir Una de las Pocas Camas de Unidad de Cuidado Intensivo? La Opinión del Público Estadounidense Sobre la Priorización de Pacientes en la Época del COVID-19.****Resumen****Objetivo**

Utilizar un experimento de elección discreta para determinar la importancia relativa que los miembros del público estadounidense dan a diferentes atributos de los pacientes en las decisiones de triaje, sobre quién debe recibir la última cama disponible en una Unidad de Cuidado Intensivo (UCI).

**Métodos**

Se utilizó una muestra representativa a nivel nacional, la cual incluyó 2000 encuestados de un panel de internet de hogares estadounidenses de YouGov. En un ejercicio hipotético, los encuestados eligieron cuál de tres pacientes con COVID-19 debería recibir una cama de la UCI, si sólo había una disponible. Los tres pacientes diferían en edad, sexo, una discapacidad similar a la de Alzheimer, y en la probabilidad de supervivencia si el paciente recibía la cama de la UCI. Un diseño experimental varió los valores de los cuatro atributos de los tres pacientes hipotéticos con COVID-19, que cada encuestado vio en cuatro ejercicios de elección.

**Resultados**

El atributo más importante del paciente para los encuestados fue la probabilidad de que el paciente sobreviviera al COVID-19 si obtiene la cama de la UCI (Intervalo de confianza de la razón de probabilidades: 4,41- 6,91). Hubo cierta heterogeneidad entre los diferentes grupos de edad de los encuestados sobre cuánto importaba la edad del paciente. Los encuestados menores de 30 años tenían mayor probabilidad de elegir pacientes jóvenes y ancianos, y menor probabilidad de seleccionar pacientes de 40 a 60 años. Para los encuestados en el grupo de edad de 30 a 49 años, a medida que la edad del paciente disminuía, su preferencia por salvar al paciente disminuyó modestamente de manera lineal.

**Conclusiones**

En este estudio de elección discreta, los encuestados se mostraron muy a favor de dar la última cama de la UCI disponible para el paciente que tiene la mayor probabilidad de sobrevivir al COVID-19. La opinión pública sugiere una pauta simple para las elecciones de los médicos basadas en la probabilidad de supervivencia en contraposición al número

de años de vida salvados. A pesar de que en este artículo nos centramos en la heterogeneidad de las preferencias entre los encuestados de diferentes grupos de edad para la asignación de la última cama de la UCI, también existe una heterogeneidad sustancial entre las preferencias de los encuestados con respecto a la importancia de que el paciente tenga una discapacidad similar a la de la enfermedad de Alzheimer (donde la identificación religiosa del encuestado es una fuente importante de heterogeneidad), y el género del paciente (donde el género y la identidad racial del encuestado son importantes).