Access this article online
Quick Response Code:

Website:
www.jehp.net

DOI:
10.4103/jehp.jehp_404_18

Using discrete choice model to elicit preference for health-care priority setting

Yaser Jouyani, Mohammad Hadiyan[1], Masoud Salehi[2], Ali Souri[3]

Abstract:

BACKGROUND: Regarding lack of resources in the health-care sector, prioritization of these resources is inevitable. The objective of the current study was to elicit public preference in prioritizing and allocating health resources using a discrete choice experiment technique, which is currently the most commonly applied method in this field of researches.

METHODS: In this discrete choice study, five attributes were selected through interview with 25 health experts to elicit people preferences in Tehran (Iran) in 2017. Eighteen choice tasks were arranged within 3 blocks, and this would be achieved with a sample size of 579. Choice data were modeled using generalized estimating equation method and STATA 14 software.

RESULTS: Five attributes including level of emergency, severity of disease, communicable, benefit from treatment, and age are the most important attributes in the prioritizing health resources from the expert's point of view. As well as among these attributes, communicable (odds ratio = 2.81) is the most important attributes from the public's point of view.

CONCLUSION: The results of this study could be very useful for prioritizing resources which is one of the most challenging measurements of the health system. By identifying the importance of each patient's characteristic, patients can be categorized in groups with different priorities, as well as the diagnosis-related group system, based on which resources are allocated.

Keywords:

Discrete choice experiment, health resource allocation, public preference

Department of Health Economics, School of Health Management and Information Sciences, Iran University of Medical Sciences, Tehran, Iran, [1]Health Management and Economics Research Center, Iran University of Medical Sciences, Tehran, Iran, [2]Department of Biostatistics, School of Public Health, Iran University of Medical Sciences, Tehran, Iran, [3]Department of Economics, Faculty of Economics, University of Tehran, Tehran, Iran

Address for correspondence:
Dr. Mohammad Hadiyan, Building of Health Management and Information Sciences in Front of Khatam Al-Nabia Hospital, Rashid Yasemi Ave., Above Vanak Sq., Valiasr, Tehran, Iran.
E-mail: hadianmohamad@iums.ac.ir

Received: 27-11-2018
Accepted: 15-01-2019

Introduction

There is no reliable evidence supporting health-care priority setting in Iran; however, policymakers are highly expected to find clear approaches for making conscious decisions on the usage of health-care resources based on their priority.[1] Nowadays, health-care providers are turning toward providing patient-centered services. Patient-centered services in health policy mean providing services in accordance with the preferences and needs of patients. In this regard, from the point of view of health policymakers it seems highly desirable to use techniques which evaluate patient preferences[2,3] While the most of decision-makers have accepted the need for prioritization in allocating health-care resources, criteria and rules for such decisions remain controversial.[4] Many attributes of people including gender, age, the responsibility, and health status without treatment in the process of setting priorities should be considered.[5,6]

In the assessing consumer preferences, researchers try to go in the direction of revealed preferences. In the health sector, due to asymmetry of information between provider, consumer, and insurance, the rate of revealed preference available for such analysis is limited. Hence, stated preference methods have been commonly used in

How to cite this article: Jouyani Y, Hadiyan M, Salehi M, Souri A. Using discrete choice model to elicit preference for health-care priority setting. J Edu Health Promot 2019;8:117.

health economics. Discrete choice experiment (DCE) is a stated preference method which allows the analysis of preferences for complex multi-attribute goods, such as health-care services, when limited market data are available.[7-9] DCE incorporates multiple characteristics for simulation of realistic scenarios by enabling different hypothetical alternatives. This method also forces individuals to make trade-offs among different set of options, unlike other techniques such as rating and ranking. Therefore, DCE as a quantitative technique enables researchers to gain a broad and in-depth insight into the relative values of every characteristic of the substitutes.[10,11]

A fundamental question in the priority setting is which criteria should be the basis for differentiation.[12] It is suggested that policymaker should consider public preferences in the health-care priority setting for several reasons, First, it is the right of every individual person to participate in defining their health care priorities. Second, obtaining knowledge of the public could directly influence on the implementation of the process. Third, it makes service providers to be accountable to service users and those who fund services.. Up to now, public participation in health-care priority setting has been limited, and information about how it has influenced the health-care organization's choices has not been explicit.[13] The objective of the current study was to elicit public preference in prioritizing and allocating health resources using a DCE technique, which is currently the most commonly applied method in this field of researches.

Methods

Discrete choice model studies attempting to elicit preferences usually consist of five steps: (1) identification of attributes and levels, (2) experimental design and scenario presentation, (3) piloting, (4) data collection, and (5) analysis of the discrete choice data.[14-17]

Identification of attributes and levels

This study used interview to establish appropriate attributes and levels in the construction of DCE. The interview was conducted with managers and health policymakers of the Ministry of Health and its affiliated universities with at least 5 years of managerial and administrative work experience. Participants were chosen using purposeful and snowball sampling methods. Data were gathered using semi-structured interviews in which researcher and participant are able to discuss more about the topic. In this study, 25 health experts (20 men and 5 women) were interviewed to select attributes which should be used in the survey. Attributes and the levels used for describing them are presented in Table 1.

Experimental design and scenario presentation

A fractional factorial design was created since using a full factorial design containing all possible combinations of the attributes and levels, listed in Table 1, was not feasible. In this study, a full factorial design would have resulted in 34 × 2 = 162 possible profiles. The SPSS ORTHOPLAN procedure was used to reduce this number to a number which is manageable by participants. To reduce the full set of scenarios down to a manageable level, the orthogonal designs were used. Orthogonal designs are commonly used as they have two appealing properties. First, orthogonality means that the correlation between two attributes is 0. Second, the level balance indicates that all attribute levels have an equal chance of being selected in fractural factorial.

We constructed 18 choice sets with two alternatives (36 scenarios) and randomly blocked them into three sets of six choices. Each questionnaire consisted of two parts that the first part included a preliminary description of the goals of the study, an instruction on how to answer the questions and gather information regarding age, gender, and educational status. The second part of questionnaires included three sets of six choices (blocks) and one dominate option. Participants were randomly

Table 1: Attribute and levels

Rows	Attributes	Levels	Description
1	Level of emergency	Elective admission Urgent admission Emergency admission	Patients need for immediate health services to prevent more health problems or death
2	Severity of disease	30% health lose 30%-70% health lose >70% health lose	Whether patients are severely affected by their disease
3	Communicable	Yes - no	Capability of being transmitted from one person to another
4	Benefit from treatment	Small (30% health gain) Moderate (30%-70% health gain) Large (>70% health gain)	The average health improvement expected from the treatment
5	Age	Young (<15) Adults (15-65) Elderly (>65)	Age of patients at the time of illness

assigned to a block and they were asked to choose their preferred option (Group A vs. Group B) for each choice task. An example of a choice task is shown in Table 2.

Piloting and internal consistency

Like all primary data-collection methods, it is recommended that DCE surveys be tested. In this research, during the design stage of the questionnaire, the validity of the questionnaire was determined by experts and its reliability was assessed in a pretest study. This included testing individuals to see if they give rational responses (internal consistency) and if they understand attributes clearly and completely.

One common test for internal consistency is to include a dominant option. In this case, one of the presented options (scenarios) is clearly dominant over the other, and respondents are expected to select that option.[18] Respondents who fail this test were referred as "inconsistent" and excluded from further analysis. Then, statistical analyses were carried out, and attributes were evaluated in terms of expected signs and directions. The success of the pilot study indicated that a similar study could be used for a larger sample sizes. Ergo respondents were expected to have the ability to consider the nature of the choice sets and to select their preferred option among the different presented scenarios.

Data collection

Sample size calculation for DCE studies in health care is complex as it depends on the verifiable values of unknown parameters estimated in the choice models. Studies have demonstrated that sample sizes of 20–30 respondents may be adequate for reliable statistical analyses.[10,19] In this study, with a design of 18 choice tasks arranged within 3 blocks, this would be achieved with a sample size of 579. On the whole, 600 questionnaires were distributed from which 21 respondents failed in dominant option test and were omitted from the analysis. The survey was administered to a sample of adults (with at least high school education/diploma degree) in Tehran during September to December 2017. The participants of the sample were selected using random probability sampling, and each of them was randomly allocated to one of the choice sets. The questionnaires were presented and filled in through face-to-face and online conversation such as Telegram. Participants were said to imagine themselves as a societal decision maker in a health-care organization and had to determine which of the two patients should be cured.

Table 2: An example of choice task

Patients attribute	Group A	Group B
Level of emergency	Emergency admission	Urgency admission
Severity of disease	30%-70% health lose	30% health lose
Communicable	No	Yes
Benefit from treatment	Small (30% health gain)	Small (30% health gain)
Age	Elderly (>65)	Adults (15-65)
Which of them do you prefer to cure?	……………	…………

Analysis of the discrete choice data

Choice data were modeled using a random utility maximization framework and STATA 14 (StataCorp. 2015. Stata Statistical Software: Release 14. College Station, TX: StataCorp LP) software. As the data are binary choice data, "1" represents the option being chosen and "0" where not chosen. As multiple observations are obtained from each individual, the data are essentially a panel or longitudinal and these regression methods are more appropriate. A regression approach for inference with longitudinal data is called generalized estimating equations (GEEs).[20,21] A regression model defines a structure for the mean response as a function of covariates. For longitudinal data, the mean has been called the marginal mean since it does not involve any additional variables such as past outcomes or random effects.[22,23]

The most commonly applied GEE is a population-averaged approach. In the panel data literature, xtgee model corresponds to population-averaged models. Xtgee is known as a useful model because of several reasons such as: is the number of statistical models that it generalizes to be used with panel data, the richer correlation structure with models available in other models, and the availability of robust standard errors, which do not usually exist in the equivalent models. We consider a logit model in which we assume that the correlation option forces the correlation parameters to be equal (exchangeable structure). In particular, xtgee fits generalized linear models and allows specifying the within-group correlation structure for the panels. There is no controversy as to the fact that the xtgee estimates are consistent, but there is some controversy as to how efficient they are. This controversy centers on how well the correlation parameters can be estimated.[24] For example, if R represents the within-group correlation for square matrix of max ({ni}) × max ({ni}), the correlation specifies the structure of R. Let R_{ts} denotes the t, s element. The independent structure is defined as

$$R_{ts} = \begin{cases} 1 & \text{if } t=s \\ 0 & \text{otherwise} \end{cases}$$

However, exchangeable structure is defined as

$$R_{ts} = \begin{cases} 1 & \text{if } t=s \\ \rho & \text{otherwise} \end{cases}$$

Since the exchangeable structure is used in this study, the regression parameter is estimated as follows:

$$B = \sum_{i=1}^{n} \frac{\partial E`}{\partial B`}(V_i^{-1})(Y - E)$$

Where B denotes coefficient, Y is dependent variable (utility), E is mean, and V_i is clearly an $n_i \times n_i$ diagonal matrix which can be factored into

$$V_i = QA_i^{1/2} R_i A_i^{1/2}$$

Where A_i is a $n_i \times n_i$ diagonal matrix, while the scale parameter Q is treated as ancillary and R_i is a correlation matrix that demonstrates exchangeable structure.[20,25]

The coefficients estimated in the model can be summed to give the overall utility for scenarios. Calculating the overall utility for each scenario allowed us to select which is likely to be most preferred overall.[14]

Results

Respondents

As in the present study, individuals were asked to answer hypothetical scenarios and no question about personal information was to be answered, so there was no problem considering ethics of research. However, this is worth mentioning that the present study has been approved by the Ethics Committees of Iran University of Medical Sciences (IR.IUMS.REC.1395.9321504005). Six hundred people entered the survey and were eligible to participate in the study, while 21 respondents failed to choose the dominant option when faced with choice sets; therefore, their data were not entered into the analysis. Each respondent replied to 6 choice sets (12 scenarios); accordingly, a total of 3474 choice observations (6948 scenarios) were obtained. Table 3 outlines some basic characteristics of the sample of 579 respondents relative to the general population of Tehran.

Table 3: Sociodemographic characteristics of respondents

Characteristics	*n* (%)
Total	579 (100)
Gender	
Male	290 (100)
Female	289 (100)
Age	
18-30	155 (27)
30-40	150 (26)
40 years and over	104 (18)
Missed	170 (29)
Marital status	
Single	281 (48.5)
Married	298 (51.5)
Educational level	
Bachelor degree	302 (52)
Master degree	210 (36)
PhD degree and over	67 (12)

Results of the discrete choice experiment

Table 4 reports the results of the GEE modeling.

A positive coefficient or an odds ratio >1 represents the increase in preferences while a negative coefficient or an odds ratio <1 indicates the decrease in preferences. Results of the GEE modeling showed that among other disease attributes, "communicable" is the most important attributes in the prioritizing health resources from the public point of view. Results of analysis showed that as the severity of the disease increases (from lower than 0.3 to higher level), the chance of resource allocation increases, but the interesting point here is that while severity of disease increases from the middle level (between 0.3 and 0.7) to the severe level (above 0.7), the chance of resource allocation decreases. All levels of attributes, except "age 15–65 years," were statistically significant and their coefficients were also in line with our expectations. Based on the results, the general model was also found to be statistically significant ($P \leq 0.001$).

Results of the scenario

What comes in the following is a summary of the total scores of scenarios. To calculate the total score and to determine the rank of each scenario, we summed up the coefficients of each scenario level for the five attributes, to see which scenario (patient), from the public point of view, has a higher priority for allocating health resources. Table 5 shows five scenarios with the highest and five scenarios with the lowest priority.

An analysis based on scenarios (hypothetical patients) allows us, in addition to possessing the importance of each attribute separately, to also have those in a patient form. The total sum of coefficients of the scenario with the highest and lowest rank was 2.7 and 0.14, respectively.

Discussion

This study was conducted aiming to consider and involve views of the public in prioritizing the allocation of health resources among different groups of patients. The findings indicated that people of our community prefer health resources to be allocated to communicable diseases as they have found that the prevention and treatment of these diseases would result in a large saving in health resources. Previous studies did not focus on "communicable" as a major attribute. It seems that one of the effective factors in the selection of attributes is the study population used for defining attributes. In our study, since the population included health-care professionals who focused on macro-health

Table 4: Analysis results

Attribute levels	Coefficient	Odds ratio	SD	*P*	95% CI
Level of emergency					
Elective admission (reference level)	0	1			
Urgent admission	0.77	2.16	0.11	<0.001	1.95-2.40
Emergency admission	0.86	2.37	0.16	<0.001	2.06-2.72
Severity of disease					
30% health lose (reference level)	0	1			
30%-70% health lose	0.44	1.56	0.08	<0.001	1.40-1.74
>70% health lose	0.14	1.16	0.03	<0.001	1.09-1.22
Communicable					
No (reference level)	0	1			
Yes	1.03	2.81	0.16	<0.001	2.50-3.16
Benefit from treatment					
Small (30% health gain) (reference level)	0	1			
Moderate (30%-70% health gain)	0.44	1.56	0.1	<0.001	1.37-1.78
Large (>70% health gain)	0.67	1.96	0.13	<0.001	1.72-2.23
Age					
Young (<15) (reference level)	0	1			
Adults (15-65)	0.09	1.10	0.07	0.13	0.97-1.24
Elderly (>65)	−0.51	0.59	0.04	<0.001	0.52-0.68

n=6948 observations . CI=Confidence interval, SD=Standard deviation, *P*=Probability level

Table 5: Estimated the highest and lowest ranked scenarios

Rank	Level of emergency	Severity of disease	Communicable	Benefit from treatment	Age	Coefficient
1	Emergency admission	>70% health lose	Yes	Large (>70% health gain)	Young (<15)	2.7
2	Emergency admission	>70% health lose	Yes	Moderate (30%-70%)	Adults (15-65)	2.56
3	Emergency admission	30%-70% health lose	Yes	Small (30% health gain) (reference level)	Adults (15-65)	2.42
4	Elective admission	30%-70% health lose	Yes	Large (>70% health gain)	Adults (15-65)	2.23
5	Urgent admission	>70% health lose	Yes	Large (>70% health gain)	Elderly (>65)	2.1
32	Urgent admission	>70% health lose	No	Small (30% health gain) (reference level)	Young (<15)	0.91
33	Urgent admission	30% health lose	No	Moderate (30%-70%)	Adults (15-65)	0.86
34	Emergency admission	30%-70% health lose	No	Small (30% health gain) (reference level)	Elderly (>65)	0.79
35	Urgent admission	30% health lose	No	Small (30% health gain) (reference level)	Elderly (>65)	0.70
36	Elective admission	>70% health lose	No	Small (30% health gain) (reference level)	Young (<15)	0.14

policymaking, they considered the "communicable" aspect of the disease as an important factor with high social impact, but definitely, in studies with micro, instead of macro, perspective, there is this tendency to be more focused on the patient's individual aspects.

Since the communicable of diseases had the highest priority in the public points of view, including it in the study was proven to be correct and necessary. However, those studies in which prevention or treatment of diseases has been discussed have considered "communicable of disease" as one of their main attributes because the first concept of contagious diseases that come to mind is the need to prevent their spread (disease prevention). Having this view, Steuten in her study in 2010 indicated the ability to prevent health problems as the most important attributes in all contexts.[26]

Findings related to the analysis of the scenarios showed that the communicability of diseases was found in all five scenarios with the highest priority while noncommunicability of diseases was seen in all five scenarios with the lowest priority which indicates the importance of the attribute "communicability of diseases" from the population's point of view.

Results related to the attribute "severity of disease" demonstrated increases in public preferences for allocating resources when the level of severity of disease rises from <0.3 to 0.3–0.7, but as the severity of the disease escalates from level 0.3–0.7 to level >0.7, the community's preference for allocating resources decreases. The public increases allocation of resources based on the increases in the level of "severity of disease," to that extent that they think its curable (≤ 0.7), but for severity of diseases more than 0.7, they prefer to allocate resources to those diseases that are more likely to be cured.

In fact, respondents believed that the closer the level of severity of disease to 1, the lower the efficiency and effectiveness of allocating resources to disease treatment. van de Wetering *et al.*[27] analyzed their study results in three separate blocks, representing that with the increase of severity of disease, preferences increase, but in the last level of this attribute (high severity of disease), preferences decrease. Results of other studies done by Blumenschein *et al.* in Canada, 2016,[28] and Green and Gerard, 2009,[29] regarding social value of health-care interventions, indicated that increases in severity of disease would increase the chances of disease to be placed in a higher priority level.

Emergency attribute actually implies the urgent need for receiving health-care services to prevent death risk. Changing from nonemergency to high emergency level and changing from nonemergency to emergency level were the second and third priorities in the health resource allocation, respectively. In the analysis of scenarios, it was also found that three scenarios with high-emergency patients had the highest priority. These results indicate that health emergency situations such as accidents and road injuries in which human lives are at risk receive high priority in health resource allocation. Given that in all hospitals and health-care centers, there are units for providing emergency services for those in needs, these results show the necessity of re-planning the current resource allocation for better management of these units. Paul Harris in his study, assessing the Australian public's preferences, found that patients' individual attributes have a great impact on prioritizing emergency patients.[30]

Analyzing "benefit from treatment," we found that as the level of this attribute increases from below to above 0.3, the chance of allocation of health resources increases. This attribute shows the amount of health gained by treatment. The amount of health that is obtained from treatment depends mostly on the treatment methods, but it also depends, to some extent, to the patients' specific characteristics and situation. The levels considered in this study were determined by taking all conditions (treatment methods, patient characteristics, etc.) into account. Other studies have used different attributes, based on the study conditions, for assessing the treatment effectiveness. For example, Gyrd-Hansen[31] in his study in Denmark, investigating whether all patients should be treated or only some? had used health status after treatment as an indicator for treatment effectiveness, while Green and Gerard[29] and Skedgel and Regier[32] used treatment effectiveness and concluded that by increasing the effectiveness of a treatment, preferences for choosing that scenario would increase.

The results about "age of the patient" showed that as the age of the patients increases from under 15 to over 65, the chance of resource allocation decreases. In terms of efficiency, these public preferences seem to be logical, since people over the age of 65 years are excluded from the community's cycle of production and are considered as consumer group, while those people under the age of 15 years will enter the production cycle in the close future and will increase community products. However, in terms of justice, it is always an element of discussion that whether it is appropriate to place the higher age group of people, for any reason, in a lower priority for treatment? Results of the present study indicated that the public prefer health resources to be allocated to lower age group, maybe with this justification that those in higher age group have used more health resources. Regarding the change of age group, from under 15 to 15–65 years, our findings showed that the chance of resource allocation will partially increase (lowest amount in our study) which was found to be insignificant. Hence, from the point of view of the public, this shift from the age group of under 15 to 15–65 years cannot have a specific impact on health resource allocation, and in fact, the public do not consider a significant difference between these two age group. Erdam in a study about health service innovation investment using public opinion found that the preferences of adults (18–30 years) were somehow more than the youth (<18 years), and preferences of these two groups were more than the elderly (above 65 years). Results of a study by Skedgel and Regier represent that preferences tend to decrease as the age of people increases.

In the present study, we had some limitations. The most important limitation was the fact that we identified the important attributes interviewing health professionals and entered them into the study to assess the community priorities. Although the results showed that the attributes included in the study were statistically significant, this does not indicate that other attributes are not important from the public views. Interview, tools, and structure provided a qualitative study, but there may be still other attributes which are important from the point of view of the public and were not considered in our study. Another limitation of our study, which exists in most of DCE studies, is to obtain highly realistic and precise data from respondents according to the type of questions. To solve this problem, we distributed the questionnaires in person and provided the necessary information and explanations to the respondent. If in that moment, the responder did not have enough time or was not able to focus on the questions, we would send them the electronic file of the questionnaire through the social network application (telegram) to fill them in as soon as possible and sent them back to the researcher easily. Furthermore, the results that were obtained for the dominant option test (only 3.5% of the respondents failed the test and were excluded from the analysis) showed that respondents had sufficient accuracy in answering questions.

According to investigations done by the research team, no similar study was found to have been conducted in Iran. So far, no internal research has used DCE method to determine important factors in the allocation of health resources.

Involving the public in the health decision -making processes, as an influential beneficiary, helped us to extract real health community preferences using the DCE method. These results could be considered as a source information for health policymakers in allocating health resources.

Conclusion

Results of this study provided significant clues to health-care providers and policymakers to ensure effective and efficient response to demands of different patients group for health-care services. In fact, the results of this study make it possible for the policymakers to use the public opinions to response to the question of who to receive what. It is recommended that other attributes that are important from the point of view of the public in the allocation of health resources should be identified and considered in the next similar studies by other researchers to complete this study outcome.

Acknowledgments
This work was part of a PHD thesis/dissertation supported by Iran University of Medical Sciences under Grant No: IUMS/SHMIS_95-9321504005. The present study has been approved by the Ethics Committees of Iran University of Medical Sciences (IR.IUMS.REC.1395.9321504005).

Financial support and sponsorship
Nil.

Conflicts of interest
There are no conflicts of interest.

References

1. Torani S, Maleki M, Hadian M, Amiresmaili M. The current status of health care priority in Iran. Payesh 2010;10:217.
2. Cheraghi-Sohi S, Hole AR, Mead N, McDonald R, Whalley D, Bower P, *et al.* What patients want from primary care consultations: A discrete choice experiment to identify patients' priorities. Ann Fam Med 2008;6:107-15.
3. Ryan M, Kolstad J, Rockers P, Dolea C. How to Conduct a Discrete Choice Experiment for Health Workforce Recruitment and Retention in Remote and Rural Areas: A User Guide With Case Studies. 20 Avenue Appia, SwitzerlandWorld Health Organization & CapacityPlus, World Bank; 2012.
4. Vass C, Rigby D, Tate K, Stewart A, Payne K. An exploratory application of eye-tracking methods in a discrete choice experiment. Med Decis Making 2018;38:658-72.
5. Fischer B, Telser H, Zweifel P. End-of-life healthcare expenditure: Testing economic explanations using a discrete choice experiment. J Health Econ 2018;60:30-8.
6. Rowen D, Labeit A, Stevens K, Elliott J, Mulhern B, Carlton J, *et al.* Estimating a preference-based single index measuring the quality-of-life impact of self-management for diabetes. Med Decis Making 2018;38:699-707.
7. González JM, Doan J, Gebben DJ, Boeri M, Fishman M. Comparing the relative importance of attributes of metastatic renal cell carcinoma treatments to patients and physicians in the United States: A discrete-choice experiment. Pharmacoeconomics 2018;36:973-86.
8. Araña JE, León CJ, Hanemann MW. Emotions and decision rules in discrete choice experiments for valuing health care programmes for the elderly. J Health Econ 2008;27:753-69.
9. Viney R, Lancsar E, Louviere J. Discrete choice experiments to measure consumer preferences for health and healthcare. Expert Rev Pharmacoecon Outcomes Res 2002;2:319-26.
10. Wong SF, Norman R, Dunning TL, Ashley DM, Lorgelly PK. A protocol for a discrete choice experiment: Understanding preferences of patients with cancer towards their cancer care across metropolitan and rural regions in Australia. BMJ Open 2014;4:e006661.
11. Jouyani Y, Bahrampour M, Barouni M, Dehnavieh R. Patient preferences for hospital quality: Case study of Iran. Iran Red Crescent Med J 2013;15:804-8.
12. van de Wetering L, van Exel J, Bobinac A, Brouwer WB. Valuing QALYs in relation to equity considerations using a discrete choice experiment. Pharmacoeconomics 2015;33:1289-300.
13. Watson V, Carnon A, Ryan M, Cox D. Involving the public in priority setting: A case study using discrete choice experiments. J Public Health (Oxf) 2012;34:253-60.
14. Shah KK, Tsuchiya A, Wailoo AJ. Valuing health at the end of life: A stated preference discrete choice experiment. Soc Sci Med 2015;124:48-56.
15. Alayli-Goebbels AF, Dellaert BG, Knox SA, Ament AJ, Lakerveld J, Bot SD, *et al.* Consumer preferences for health and nonhealth outcomes of health promotion: Results from a discrete choice experiment. Value Health 2013;16:114-23.
16. Erdem S, Thompson C. Prioritising health service innovation investments using public preferences: A discrete choice experiment. BMC Health Serv Res 2014;14:360.
17. Lancsar E, Wildman J, Donaldson C, Ryan M, Baker R. Deriving distributional weights for QALYs through discrete choice experiments. J Health Econ 2011;30:466-78.
18. Ali S, Ronaldson S. Ordinal preference elicitation methods in health economics and health services research: Using discrete choice experiments and ranking methods. Br Med Bull 2012;103:21-44.
19. de Bekker-Grob EW, Bliemer MC, Donkers B, Essink-Bot ML, Korfage IJ, Roobol MJ, *et al.* Patients' and urologists' preferences for prostate cancer treatment: A discrete choice experiment. Br J Cancer 2013;109:633-40.
20. Hardin JW. Generalized estimating equations. Encyclopedia of Statistics in Behavioral Science: chichester, wiley,2005, 2:721-9.
21. Ziegler A. Generalized Estimating Equations. New York, NY 10013, USA:Springer Science & Business Media; 2011.
22. Stata A. Stata Base Reference Manual Release 14: Stata Press, 4905 Lakeway Drive, College Station, Texas 77845;2015.
23. Wang M. Generalized estimating equations in longitudinal data analysis: A review and recent developments. Adv Stat 2014;2014:11.
24. Wang YG, Fu L. Selection of working correlation structure in generalized estimating equations. Stat Med 2017;36:2206-19.
25. Press S. Stata Longitudinal-Data/Panel-Data Reference Manual: Release 11: Stata Press, 4905 Lakeway Drive, College Station, Texas 778452009.
26. Steuten L, Buxton M. Economic evaluation of healthcare safety: Which attributes of safety do healthcare professionals consider most important in resource allocation decisions? Qual Saf

Health Care 2010;19:e6.
27. van de Wetering EJ, van Exel NJ, Rose JM, Hoefman RJ, Brouwer WB. Are some QALYs more equal than others? Eur J Health Econ 2016;17:117-27.
28. Blumenschein P, Lilley M, Bakal JA, Christian S. Evaluating stakeholder's perspective on referred out genetic testing in Canada: A discrete choice experiment. Clin Genet 2016;89:133-8.
29. Green C, Gerard K. Exploring the social value of health-care interventions: A stated preference discrete choice experiment. Health Econ 2009;18:951-76.
30. Harris P, Whitty JA, Kendall E, Ratcliffe J, Wilson A, Littlejohns P, *et al.* The importance of population differences: Influence of individual characteristics on the australian public's preferences for emergency care. Health Policy 2018;122:115-25.
31. Gyrd-Hansen D. Investigating the social value of health changes. J Health Econ 2004;23:1101-16.
32. Skedgel C, Regier DA. Constant-sum paired comparisons for eliciting stated preferences: A tutorial. Patient 2015;8:155-63.