Postprint: Research Advances on Discrete Choice Experiments in Health Human Resources

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Abstract

This study searched, compiled, and analyzed English-language literature from 2000-2020 on the application of discrete choice experiments in the field of health human resources, with databases including Web of Science, PubMed, and Baidu Scholar, resulting in 44 included articles. This paper comprehensively introduces the general characteristics of the included studies, including study subjects, analytical models, and research findings, and develops a conceptual framework of job attributes. It finds that there is substantial heterogeneity in research findings within this field, making it difficult to draw unified conclusions. Furthermore, the application of discrete choice experiments in health human resources still requires further global promotion; relevant research remains quite limited, and the obtained evidence needs confirmation through additional studies. This paper also proposes several recommendations for experimental design to provide references for future research, such as employing iterative approaches in the qualitative research component and quantifying level descriptions whenever possible.

Full Text

A Literature Review on Discrete Choice Experiments in Human Resources for Health

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Abstract

This review examined English-language studies applying Discrete Choice Experiments (DCE) in human resources for health published between 2000 and 2020. Searches were conducted in Web of Science, PubMed, and Baidu Scholar, yielding 44 eligible studies. We comprehensively synthesized study characteristics, including respondent populations, analytical models, and findings, and developed a conceptual framework of job attributes. The results revealed considerable heterogeneity across studies, precluding unified conclusions, and indicated that DCE applications in this field require further global promotion. Evidence remains limited and requires confirmation through additional research. We propose recommendations for experimental design to inform future studies, such as employing iterative approaches in qualitative research phases and quantifying attribute levels whenever possible.

Keywords: discrete choice experiments; human resources for health; health workers; doctors; nurses

Introduction

Shortages and maldistribution of health human resources compromise the equity and accessibility of health services, representing a widespread and consequential global health challenge [?]. The world currently faces a deficit of 7.2 million nurses, doctors, and midwives, projected to increase to 12.9 million by 2035 [?]. In Bangladesh, urban areas concentrate 35% of all physicians but only 14.5% of the national population, while in Ghana, 87.2% of general practitioners work in cities where 66% of the population resides in rural areas [?]. Attracting and retaining health workers in rural regions is particularly critical. The World Health Organization (WHO) has proposed a four-dimensional framework for addressing rural retention: education, regulatory mechanisms, financial incentives, and personal/professional development opportunities [?]. WHO emphasizes that countries should tailor interventions to their specific contexts, labor market conditions, and local needs [?].

Effective, targeted policy development requires consideration of multiple factors, including health workers' own job preferences. Discrete Choice Experiments (DCE) provide robust methodological foundations for investigating these preferences. Originating in the late 1950s within microeconometrics, DCE has evolved into a powerful tool for studying individual choice behavior.

Initially applied to market and transportation research, DCE in health services can examine patient preferences for treatment modalities, community preferences for general practitioner service delivery, stakeholder preferences for health surveillance system operations, and policymakers' priorities for health policy development [?]. The first applications of DCE to health human resources emerged in the late 1990s [?]. DCE methodology was introduced to China relatively recently and remains in the application phase.

Grounded in consumer theory, DCE posits that goods, services, and jobs consist of various attributes described at different levels. For example, the job attribute "availability of basic equipment" can be described as "adequate" or "inadequate." DCE identifies preference patterns for different attribute levels, provides quantitative information on level preferences (β coefficients), trade-off information (Willingness to Pay, WTP), and calculates probabilities of choosing specific jobs (Uptake Rates), representing a mixed-methods approach that validates the relative importance of attributes [**?**].

As a comprehensive methodology, DCE employs qualitative research, literature review, and pilot testing to identify relevant attributes and levels. Qualitative research is crucial to ensure selected attributes and levels adequately represent target population perspectives while remaining policy-actionable and forward-looking [**?**]. Based on selected attributes and levels, choice sets are generated, typically comprising 4 to 20 "choice tasks." In health worker preference studies, each task usually presents two hypothetical jobs (A and B) for respondents to choose between. Tasks can be generic or labeled. [Figure 1: see original paper] illustrates generic "Job A" and "Job B" options; replacing these with "Rural Clinic" and "Urban Hospital" would constitute a labeled design.

Choice sets must satisfy orthogonality, level balance, and minimal overlap. Various design methods achieve these properties, including fractional factorial designs, orthogonal main effects designs, and D-efficiency designs. Software such as SAS, NGene, and Sawtooth can generate appropriate choice sets. Data analysis employs multiple statistical models, including Mixed Logit Model (MXL), Conditional Logit Model (CLM), Generalized Multinomial Logit Model (G-MNL), and Latent Class Model (LCM). G-MNL extends MXL by using a single parameter to adjust the parameter distribution. MXL accommodates respondent heterogeneity more flexibly than CLM, while LCM enables stratified analysis based on demographic characteristics to explore preference heterogeneity.

Methods

1.1 Electronic Databases Searched Web of Science, PubMed, and Baidu Scholar.

1.2 Search Keywords Discrete choice experiment, human resources for health, health technicians, doctors, nurses.

1.3 Publication Years 2000–2020.

1.4 Inclusion and Exclusion Criteria Peer-reviewed, English-language articles reporting complete DCE results were included, provided they met at least

90% of the validity criteria proposed by Kate L. Mandeville et al. [?] (Table 1).

English-language DCE studies with full text applications in health human resources were initially identified. Titles and abstracts were screened, followed by full-text review. A "snowballing" approach examined references of included articles. Ultimately, 44 studies were included (Figure 2 [Figure 2: see original paper]).

Results

2.1 Publication by Country Among the 44 included studies, 12 (27%) were from high-income countries: Australia (6), Denmark and Norway (2 each), and the United Kingdom and Germany (1 each). Thirty-two studies (73%) were from low- and middle-income countries: one multinational study covering Kenya, South Africa, and Thailand; 12 Asian studies (38%) including China (3), India (2), and one each from Laos, Indonesia, Timor-Leste, Thailand, Iran, Vietnam, and Nepal; 17 African studies (53%) with three each from Ghana and Uganda, two each from Tanzania and Malawi, and one each from Kenya, Mozambique, Burkina Faso, Cameroon, Senegal, Zambia, and Sudan; and two South American studies from Peru (6%) (Figure 3 [Figure 3: see original paper]).

2.2 Publication Years One article each was published in 2001 and 2008, peaking at eight articles in 2015, followed by a gradual decline with a small resurgence (six articles) in 2019 (Figure 4 [Figure 4: see original paper]).

2.3 Study Populations and Sample Sizes Primary study populations included doctors, nurses, medical and nursing students, followed by community health workers, midwives, allied health professionals, pharmacists, midwifery students, laboratory students, and pharmacy students (Table 2). Doctors comprised both general practitioners and specialists, including neurosurgeons, obstetricians/gynecologists, physiotherapists, speech pathologists, and psychiatrists.

High-income countries generally reported larger sample sizes than low- and middle-income countries.

2.4 Choice Task Formats Six studies used labeled designs; the remainder employed generic formats.

2.5 Number and Selection of Attributes and Levels Studies included 4–8 attributes with 2–4 levels each. Income (salary) was universally included. Workplace location was another common attribute, alongside workload, social support, and others.

Attribute selection varied across economic and cultural contexts. High-income country studies frequently included team-based practice and workload as attributes. In low- and middle-income countries, the most common attributes were learning/training opportunities, followed by housing, equipment/drug availability, transportation, career advancement opportunities, management climate, children’ s education, private practice opportunities, and employment status recognition (permanent positions). Context-specific attributes included library facilities in Iran and supervisory support in Uganda.

2.6 Analytical Models MXL was most frequently used (50% of studies), followed by CLM, G-MNL, and some applications of LCM.

2.7 Attribute Weighting by Study Populations Cross-study comparison of attribute importance (beyond income) was inappropriate due to varying attributes and populations. For example, a multinational study found that nursing students in Kenya and South Africa prioritized educational opportunities and rural allowances, while Thai respondents most valued improved health insurance [?]. However, income was universally included. Compared to low- and middle-income countries, high-income country respondents placed greater weight on non-income attributes. Sivey et al. found that increasing job technical content was the most attractive attribute for Australian junior doctors considering general practice, increasing uptake by 13 percentage points—more than modest salary increases [?]. Norwegian research indicated young doctors valued leisure time allocation more than income [?]. In low- and middle-income countries, Rockers et al. found Lao nurses prioritized income and permanent employment status [?], while Huicho et al. identified income, working in health centers rather than lower-level clinics, and professional training funding as key factors enhancing rural job attractiveness for Peruvian nurses and midwives [?].

Subgroup preferences also varied. Employed nurses placed less emphasis on housing and transportation than nursing students [?]. Young doctors with student loans prioritized income more highly [?]. Physicians with rural experience valued 45% salary increases and proximity to home provinces but were less concerned about reducing night shifts [?]. Some null findings emerged: female physicians and those with children did not differ significantly in work time preferences [?].

Parameter reporting varied across studies. Most reported coefficient β values (indicating attribute importance), while some reported odds ratios. Some studies omitted WTP estimates or policy simulation probability analyses (Uptake Rates); those conducting probability analyses often presented single-policy rather than policy-package effects.

Discussion

Health workforce shortages and maldistribution are global challenges, yet DCE applications in this field remain limited. Our review found that high-income countries generally reported larger sample sizes, likely reflecting more mature health workforce data platforms.

Attribute selection necessarily varies across labor market contexts. We synthesized and organized attribute characteristics into a conceptual framework (Figure 5 [Figure 5: see original paper]) comprising four domains: societal, job-related, professional development, and lifestyle.

Societal domain: Hospital size, social support/respect, employment status recognition (permanent positions).
Job-related domain: Workplace location, working conditions, workload, management climate, teamwork, supervisory support (for community health workers).
Professional development domain: Promotion timeline, training (continuing education) opportunities, academic and research opportunities.
Lifestyle domain: Income, housing, transportation, children' s education.

Hospital size was categorized under the societal domain because individuals and society psychologically associate large hospitals with higher social status. Employment status recognition affects both benefits and social belonging, warranting its societal classification. One study distinguished management climate as hierarchical versus interactive, with interactive climates preferred [?], as harmonious work environments enhance motivation. Teamwork is crucial for work support, facilitating both job performance and well-being. Specific attribute selection depends on local labor market conditions and priorities of policymakers and health workers.

Notably, Holte et al. found Norwegian general practitioners' income preferences followed a nonlinear distribution consistent with reference dependence theory, where losses and gains are evaluated relative to a reference point. Respondents weighted income losses three times more heavily than equivalent gains [?].

Regarding DCE validity and reliability, Doiron et al. used a two-stage approach to examine temporal stability of stated preferences, finding preferences sufficiently stable to inform policy priority-setting, though income attribute instability requires further investigation [?]. "Attribute non-attendance" (ANA)—where respondents use simplified strategies ignoring one or more attributes—was examined by Lagarde (2012), who found most respondents considered only one or two attributes. However, comparing models accounting for ANA with standard models revealed no differences in estimated probabilities, suggesting DCE can generate "unbiased policies," though confirmation is needed [?]. Heidenreich et al. (2017) investigated whether ANA represents heuristic decision-making or true preferences, concluding ANA generally reflects genuine preferences and that concerns about inappropriate policy recommendations are unfounded [?].

In summary, this review comprehensively described DCE applications in health human resources, including study populations, sample sizes, choice task formats, attribute/level selection, analytical models, and attribute weighting. We developed a conceptual framework of job attributes while identifying the need for broader global DCE application, given limited evidence requiring confirmation. We also reviewed methodological validity studies, finding DCE can support policy recommendations but requires more research. Considering WHO' s promotion of DCE, we offer design recommendations for future studies.

4.1 Qualitative Research

Most studies conducted qualitative work with target populations, including focus group discussions (FGD) and in-depth interviews. Some employed iterative team discussions involving interviewers, analysts, researchers, and DCE technical advisors [?]. Coast et al. used an iterative approach: first iteration combined expert opinion with exploratory work to validate selected attributes, emphasizing comparative techniques to identify novel data characteristics; second iteration continued attribute discussion to determine necessary additions or deletions; third iteration ensured comprehensive attribute elaboration [?].

Mullei et al. combined quantitative (Likert scale) and qualitative methods to identify job attributes, representing a valuable approach [?]. However, strong evidence supporting the validity of such qualitative work is lacking, limiting generalizability and utility for other researchers. This field requires theoretical grounding or at least more systematic methods [?]. Attributes and levels should be finalized through pilot testing [?], with rigorous, repeated piloting facilitating attribute-level balance.

4.2 Experimental Design

Labeled designs help respondents connect tasks to real-world contexts and reduce attribute-level confusion, with label meanings aiding decision-making. However, researchers cannot confirm whether label interpretations align with respondents' understanding, and labels correlate with attributes/levels, complicating separation of their effects in analysis. For evaluating perceptions of identical job attributes across different positions or investigating preferences for specific job types, this correlation is not problematic. Generic designs better suit research interests comparing trade-offs among different attributes for a single job type [?].

Choice tasks varied: most presented two options (Job A vs. Job B) (Figure 1), while some used three or four options or mixed formats. For example, Peruvian research on doctors' rural job preferences used three-option labeled designs [?], and Lagarde et al. used four-option labeled designs [?]. However, increasing options may reduce response quality [?].

Based on consumer theory, choice tasks should include an opt-out option (Figure 1). Omitting this artificially inflates choice probabilities and biases WTP estimates, as health workers realistically face multiple options, including remaining in current positions or leaving the profession entirely—a particularly relevant consideration for new graduates.

Two-stage choice designs are recommended when respondents' employment status is known. Stage one presents forced choice between two options (Job A vs. Job B). Stage two adds an opt-out option. This approach retains useful information even when respondents opt out. Researchers should prioritize opt-out inclusion to improve WTP estimation accuracy [**?**], though few included studies employed this method.

4.3 Job Attributes and Levels

Attribute and level specification must be understandable to respondents to facilitate meaningful trade-offs. Concepts and ranges require clear definition; for example, income specifications should clarify whether referring to monthly or annual salary, take-home (post-tax) pay, and whether performance bonuses are included—some studies treat performance bonuses as separate attributes.

Selection should consider target populations, policymakers, and local labor market characteristics, as locally appropriate interventions outperform standardized approaches. Attributes and levels must be operationally translatable into policy. Questionnaire instructions are critical, as respondents may interpret attributes differently from designers.

Income is nearly universally included, as it is a primary determinant of job choice and the basis for WTP calculations. Attributes must be non-overlapping and one-dimensional (mutually independent), representing single characteristic facets to maximize information extraction and interpretability. Omitting key attributes introduces bias, requiring trade-offs against including too many attributes, which may increase response variability [**?**].

Considering design simplification, task complexity, non-compensatory decision rules, and survey costs, 5–8 attributes are typical. No studies have examined multi-attribute DCE designs in health human resources, though Witt et al. explored 11 attributes in quality-of-life research using blocked orthogonal designs, requiring further validation [**?**].

Levels (typically 2–4 per attribute) should reflect attribute ranges, encompass current job characteristics, and capture target population expectations (forward-looking). Level spacing must be appropriate—too narrow or wide affects judgment. Quantitative descriptions are preferable; for continuing education attributes, "twice annually" versus "once every two years" is clearer than "few" versus "many."

In China' s context, permanent employment status (编制) coexists with contract-based employment in the same institutions with substantial benefit differences.

DCE studies have included employment status as an attribute, but findings on its importance vary, warranting further investigation.

In conclusion, DCE as a stated preference method can overcome real-world choice constraints to inform policy, but design quality ultimately affects result reliability. This review has limitations: exclusion of grey literature and conference proceedings may have missed relevant studies, and inclusion of only English-language articles introduces language bias.

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Tables

Table 1. Literature Inclusion and Exclusion Criteria

Inclusion Criteria	Exclusion Criteria
Peer-reviewed, English-language articles, no country restrictions	Non-peer-reviewed, non-English articles
Articles reporting complete DCE results	Articles reporting only qualitative methods/results; articles without attribute/level descriptions
Meeting \$ \$90% of Kate L. Mandeville et al.' s "study validity assessment criteria"	Failing to meet \$ \$90% of Kate L. Mandeville et al.' s "study validity assessment criteria"

Table 2. Study Populations

Category	Subgroups
Employed health workers	Doctors, nurses, community health workers, midwives, allied health professionals, pharmacists
Students	Medical students, nursing students, midwifery students, laboratory students, pharmacy students

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Appendix: Summary of Included Studies

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
1	Primary care providers	Jilin, Shandong, Anhui, Chongqing, Shaanxi (China)	2015	Generic	Mixed logit model	Valued income, benefits, equipment, and community respect; younger providers valued training and career development
2	Medical students	Shandong (China)	2018	Generic	Mixed logit model	Valued urban locations and tertiary hospitals; preferred low workload and good work environment

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
3	Nursing students	Shandong (China)	2019	Generic	Mixed logit model	Valued low workload and good work environment
4	Young doctors	Australia	2012	Generic	Mixed logit model	Valued increased income and technically rich work; 13% more likely to choose general practice with increased technical content
5	General practitioners	Australia	2013	Generic	Mixed logit model	Rural jobs attractive only with $ $130% salary increase
6	Rural general practitioners	Australia	2014	Generic	Mixed logit model	Most valued relief support, retention allowances, and skill development

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
7	Allied health professionals	Australia	2015	Generic	Conditional logistic regression; Latent class regression model	Most valued practice autonomy, followed by fewer night shifts and career development
8	General practitioners	Australia	2015	Generic	Generalized multinomial logit model	Valued autonomy and workplace violence management
9	General practitioners	Australia	2020	Generic	Generalised multinomial logit model	Valued public sector employment
10	General practitioners	UK (England)	2001	Generic	Random effects probit model	Valued night shift arrangements
11	Young doctors	Norway	2010	Generic	Least square regression model	Most valued income changes, followed by children' s education location and fewer on-call duties

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
12	General practitioners	Germany	2014	Generic	Mixed logit model	Financial incentives effective for productivity; preferred 2-GP practices
13	General practitioners	Denmark	2015	Generic	Mixed logit model	Valued peer exchange, application of new knowledge, and guaranteed 10 days of annual CME with 50% individual/50% centralized planning
14	Final-year medical students and interns	Norway	2015	Generic	Mixed logit model	Non-monetary incentives more effective than monetary

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
15	General practitioners	Norway	2016	Generic	Mixed logit model	Weighted income losses more heavily than equivalent gains (reference dependence)
16	Nursing students and nurses	Laos	2013	Generic	Mixed logit model	Both groups valued permanent employment and housing/transportation; nursing students valued salary more
17	Nurses and midwives	Peru	2012	Generic	Multiple conditional logistic regression	Valued income, facility type, and training scholarships
18	Doctors	Peru	2012	Generic	Multiple conditional logistic regression	Valued income, facility type, and training scholarships

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
19	Community health assistants	Uganda	2013	Generic	Mixed logit model	Valued housing, transportation, and equipment
20	Health workers	Uganda	2016	Generic	Mixed logit model	All valued salary, equipment quality, and management support; medical/lab students also valued future training funding; pharmacy students valued dual practice opportunities
21	Community health workers	Uganda	2014	Generic	Mixed logit model	Valued tools, T-shirts, badges, and bicycles; then cell phones without call restrictions

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
22	Community health workers	Tanzania	2016	Generic	Multinominal logit model; Mixed logit model	Valued income and community recognition
23	Community health workers	Tanzania	2011	Generic	Logit model	Most valued continuing education, followed by housing
24	Community-based mobilizers	Tanzania	2019	Generic	Conditional logistic regression	Valued ID cards, bimonthly training, leadership visits, and uniform subsidies
25	Public sector nurses	Malawi	2008	Generic	Multivariate model	Valued career advancement, housing, and facility equipment
26	Medical, nursing, midwifery, and allied health students	Malawi	2016	Generic	Latent class model	Those not staying in Malawi valued specialty training; core specialty groups valued timely training

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
27	Clinical officers	Kenya	2016	Generic	Conditional logit model	Most valued training after 3 years of work, followed by good equipment and 30% salary increase
28	Health students	Indonesia	2016	Generic	Mixed logit model	Different student groups valued different attributes
29	Non-physician health professionals	Mozambique	2015	Generic	Conditional logit model	Most valued government-provided housing, followed by education opportunities and equipment
30	Health workers	Burkina Faso	2014	Generic	Probit logistic regression model	Housing most important
31	Health workers	Timor-Leste	2016	Generic	Conditional logit model	Most valued career development and skills training

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
32	Doctors and nurses	India	2013	Generic	Mixed logit model; Latent class model	Large subgroup differences; doctors less sensitive to income increases than nurses; rural-born and those accepting rural work valued different attributes
33	Community health workers	India	2019	Generic	Multinominal logit model; Latent class model	Valued training, fixed income, and free family health checkups
34	Doctors	Cameroon	2015	Generic	Mixed logit model	Valued career advancement, housing, and equipment
35	Neurosurgeons	Iran	2015	Generic	Random effects probit model	Valued salary increases, dual practice, and equipment

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
36	Health professionals	Senegal	2019	Generic	Mixed logit model	Valued permanent contracts, equipment, and training opportunities
37	Doctors	Vietnam	2011	Generic	Mixed logit model	Continuous education and equipment improvement most effective
38	Obstetricians, pediatricians, and anesthetists	Vietnam	2019	Generic	Multinominal logistic regression model	Valued teams including pediatricians and anesthetists, children's primary/secondary education, and private practice opportunities
39	Final-year medical and nursing students; primary care staff	Sudan	2018	Generic	Mixed logit model	Valued overseas training scholarships, advanced equipment, and on-site supervision

No.	Study Population	Location	Year	Design Type	Analytical Model	Key Findings
40	Medical, nursing, midwifery, laboratory, and pharmacy students	Uganda	2012	Generic	Mixed logit model	All valued salary, equipment quality, and management support; medical and lab students also valued future training funding; pharmacy students valued dual practice

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.