Discrete Choice Experiments: opportunities and challenges

DataX Seminar Series

Yuanyuan Gu

Associate Professor

Macquarie University Centre for the Health Economy (MUCHE)

30 August 2023

Overview

What is DCE?

Choice modelling

- Choice modeling is the theory of individual decisions among discrete alternatives and its empirical derivatives in the form of measurement procedures and estimation methods

- It models individuals' choices and decisions about healthcare, transport, purchases, lifestyle, and other activities.
    - Determining factors of the choice (attributes of the object and characteristics of the individuals): prediction (e.g., demand)
    - Trade-offs between attributes: valuation (e.g., willingness to pay)

- Data: revealed preference (RP) vs stated preference (SP)

- RP: what people did

- SP: what people stated they would do

Discrete Choice Experiment (DCE)

- DCE is a SP method - other SP methods include ranking, rating, etc.
- A survey experiment approach
- Respondents are presented with a series of hypothetical, but realistic choice sets with each alternative described by a bundle of attributes, each with a different level. Respondents are then asked to choose their most preferred option
- Based on a premise that the choices people make are informative about what they value

	Treatment A	Treatment B
Mode of administration	6-month subcutaneous injection	Weekly oral tablet
Adverse effects of treatment (1 in 50 patients would suffer the adverse effect)	Gastro-intestinal disorders	Flu-like symptoms
Treatment efficacy in reducing the risk of fracture	30%	40%
Out-of-pocket cost per year	520 Yuan per annum	26,000 Yuan per annum

A little bit of history: theory

- Choice modeling theory developed independently by economists (Daniel McFadden) and mathematical psychologists (Louis Leon Thurstone, Duncan Luce and Anthony Marley)

- Random utility theory: decision makers maximise their utility through choices

- Multinomial choice framework (conditional logit model)

Conditional logit analysis of qualitative choice behavior

DANIEL McFADDEN[1]

UNIVERSITY OF CALIFORNIA AT BERKELEY
BERKELEY, CALIFORNIA

I. Preferences and Selection Probabilities
II. Conditional Logit Estimation
III. Statistical Properties
IV. An Empirical Application
Shopping Choice of Mode
Shopping Choice of Destination
Shopping Trip Frequency
Appendix: Proofs of Statistical Properties
References

A fundamental concern of economics is understanding human choice behavior. Models or hypotheses are formed on the nature of decision processes, and are evaluated in the light of observed behavior. This task is complicated

MACQUARIE University

A little bit of history: DCE

- In transport and marketing, conjoint analysis (configuration of goods using attributes) and design of experiments (using a small number of choice tasks to estimate preferences) were used to predict demand for new products in 1960s and 70s.
- In 1980s, Jordan Louviere and David Hensher formalized these methods based on random utility theory – the beginning of DCE

Design and Analysis of Simulated Choice or Allocation Experiments in Travel Choice Modeling

JORDAN J. LOUVIERE AND DAVID A. HENSHER

A new approach for modeling traveler trade-offs and choices is proposed, described, and illustrated. Based on research in psychology, marketing, and economics, a method for developing discrete choice models from controlled laboratory simulation experiments is developed and presented. The method borrows statistical theory from discrete choice theory in econometrics and from the design of statistical experiments to marry work in trade-off analysis with choice analysis. The method is illustrated by means of several travel-choice-related examples that involve choice of mode and destination. Recent evidence of validity in forecasting the actual behavior of real markets is reviewed in support of the approach.

Since the early 1970s, the study of revealed-choice behavior based on the random utility derivations of discrete choice theory in econometrics (1-6) has gained a following in the analysis and forecasting of travel behavior. If real choice data satisfy the conditions assumed in the statistical choice models, it is possible to derive aggregate-level trade-offs and to simultaneously forecast choice behavior. Hence, methods based on revealed choice have high external validity and practical applicability to strategic policy problems.

Other approaches have recently gained attention--notably, laboratory simulation methods such as variations of conjoint measurement or trade-off analysis (7-9) and functional measurement (10-15), which are the primary methods of approach for developing quantitative descriptions of multiattribute individual

Usefulness of DCEs

Why do we use the DCE?

Revealed preference

Revealed preference

What factors affect the choice of transportation method?

Attributes of the transportation method:

- Cost
- Speed
- Safety

Characteristics of the traveller:

- Gender
- Age
- Income
- Travel distance

How do these factors impact on the choice?

- Data collection for each travel with all the factors (need lots of observations)

Revealed preference issues

- Key variables (e.g. price) do not have variation
- Key variables are missing (potential endogeneity problems)
- The product is not available yet: no data at all

Why do we use DCEs?

- When revealed preference data is not available or of poor quality (little variations, data missing, etc.)
- DCEs generate choice data regardless of the existence of the products
- It is an experiment so we can ensure variations and control endogeneity
- It is a survey approach so we can always get the choice data and control/assess quality
- We can also collect a large number of individual characteristics to assess their impact on the choice (preference heterogeneity)

DCE applications

- Early applications: marketing, transportation, environment research
- Now widely used – whenever there is a need to assess people's preferences and understand their needs.
- One of the most popular methods in healthcare research (where revealed preference data are often not available)
- Application examples：
  - Patient preference for medical treatments or healthcare services
  - Preference for healthcare priority setting (value judgement)
  - Consumer preference for health insurance products
  - Job preference of healthcare workers

Cast study 1

Patient preference for pharmaceutical treatments

Springer Link

Original Paper | Published: 31 July 2019

Chinese patients' preference for pharmaceutical treatments of osteoporosis: a discrete choice experiment

Lei Si, Liudan Tu, Ya Xie, Andrew J. Palmer, Yuanyuan Gu, Xuqi Zheng, Jiamin Li, Qing Lv, Jun Qi, Zhiming Lin, Mingsheng Chen, Jieruo Gu & Mickaël Hiligsmann

Archives of Osteoporosis **14**, Article number: 85 (2019) | Cite this article

Abstract

Summary

While adherence to osteoporosis treatment is low, patients' preference for osteoporosis treatment is unknown in Chinese patients. Chinese patients are willing to receive treatments with higher clinical efficacy and lower out-of-pocket cost. In addition, annual intravenous infusion and 6-month subcutaneous injection are preferred over weekly oral tablets.

Purpose

This study was performed to elicit Chinese patients' preferences for osteoporosis medication treatment and to investigate the heterogeneities of the preferences in subgroups.

Attributes and levels

Treatment efficacy in reducing the risk of fracture	20%
	30%
	40%
	50%
Out-of-pocket cost per year, RMB Yuan[a]	520
	2600
	4160
	5200
	26,000
Adverse effects of treatment[b]	Flu-like symptoms
	Skin reactions
	Gastrointestinal disorders
Mode of administration	Daily oral tablet
	Daily nasal spray
	6-month subcutaneous injection
	Yearly intravenous infusion
	Weekly oral tablet

[a]One RMB Yuan = 0.15 US dollars in 2018

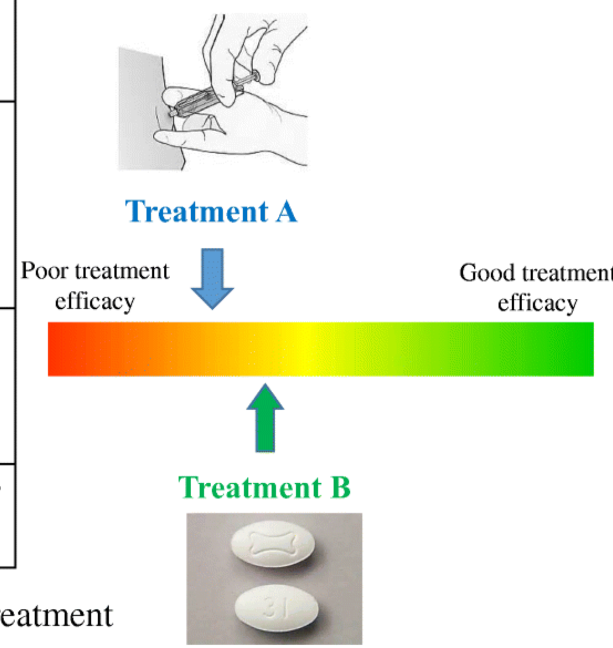
[b]Adverse effects of treatment were assumed to occur in 1 of every 50 patients undergoing treatment. Each of these adverse effects was relatively mild, disappeared after a few days and had no long-term or severe consequences

A choice set

	Treatment A	Treatment B
Mode of administration	6-month subcutaneous injection	Weekly oral tablet
Adverse effects of treatment (1 in 50 patients would suffer the adverse effect)	Gastro-intestinal disorders	Flu-like symptoms
Treatment efficacy in reducing the risk of fracture	30%	40%
Out-of-pocket cost per year	520 Yuan per annum	26,000 Yuan per annum

Which treatment would you choose? Treatment A ☐ Treatment B ☐ No treatment ☐

(Tick one box only)



Case study 2

Value judgement in health care priority setting: whose life is more valuable?

Journal of Health Economics 70 (2020) 102303

Contents lists available at ScienceDirect

Journal of Health Economics

journal homepage: www.elsevier.com/locate/econbase

ELSEVIER

The relative value of different QALY types

Emily Lancsar[a,*], Yuanyuan Gu[b], Dorte Gyrd-Hansen[c], Jim Butler[d], Julie Ratcliffe[e], Liliana Bulfone[f], Cam Donaldson[g]

[a] *Department of Health Services Research and Policy, Research School of Population Health, Australian National University, Australia*
[b] *Centre for the Health Economy, Macquarie University, Australia*
[c] *Centre of Health Economics Research, Department of Public Health, University of Southern Denmark, Denmark*
[d] *Health Research Institute, University of Canberra, Australia*
[e] *Health and Social Care Economics Group, College of Nursing and Health Sciences, Flinders University, Australia*
[f] *Deakin Health Economics, Deakin University, Australia*
[g] *Yunus Centre for Social Business and Health, Glasgow Caledonian University, United Kingdom*

ARTICLE INFO

Article history:
Received 24 October 2018
Received in revised form 26 January 2020
Accepted 29 January 2020
Available online 13 February 2020

JEL classification:
C35
I1
I18

Keywords:

ABSTRACT

The oft-applied assumption in the use of Quality Adjusted Life Years (QALYs) in economic evaluation, that all QALYs are valued equally, has been questioned from the outset. The literature has focused on differential values of a QALY based on equity considerations such as the characteristics of the beneficiaries of the QALYs. However, a key characteristic which may affect the value of a QALY is the type of QALY itself. QALY gains can be generated purely by gains in survival, purely by improvements in quality of life, or by changes in both. Using a discrete choice experiment and a new methodological approach to the derivation of relative weights, we undertake the first direct and systematic exploration of the relative weight accorded different QALY types and do so in the presence of equity considerations; age and severity. Results provide new evidence against the normative starting point that all QALYs are valued equally.

Attributes and levels

Attributes (Short name)	Levels
Age of people who will receive this treatment if treatment is funded ("age")	Infant (0–12 months) Child (1–12 years) Teen (13–17 years) Young adult (18–29 years) Adult (30–49 years) Older adult (50–59 years) Senior (60–74 years) Older senior (75+ years)
Quality of Life (QoL) without this treatment ("QoL")	5 % (very severe health problems) 30 % (severe health problems) 60 % (moderate health problems) 90 % (mild health problems)
Remaining life expectancy (LE) without this treatment ("LE")	0–3 months 4 months–2 years 3–5 years The medical condition has no effect on LE
Average number of QALYs gained per person with this treatment ("QALY")	0.01 of a QALY 0.5 of a QALY 1 QALY 4 QALYs
Type of QALYs gained with this treatment ("Type")	Life extension Improvement in QoL Mixture of life extension and improvement in QoL Life extension but with reduced QoL

A choice set

MACQUARIE University

Below are two treatments for people with medical conditions. Given that only one treatment can be funded, which treatment would you choose to fund *so it's available to you and all Australians?*

	Treatment A	Treatment B
Age of the people who will receive this treatment if funded	Adult (30-49 years)	Young adult (18-29 years)
Quality of life without this treatment	5% (very severe health problems)	60% (moderate health problems)
Remaining life expectancy without this treatment	4 months – 2 years	0-3 months
Average number of QALYs gained per person with this treatment	0.5 of a QALY	0.5 of a QALY
Type of QALYs gained with this treatment are due to	Life extension	Mixture of life extension and improvement in quality of life
	Fund this?	Fund this?

Case study 3

Medical Brain Drain: Italian young doctors’ job preferences

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

MACQUARIE University

DISCUSSION PAPER SERIES

IZA DP No. 16243

Medical Brain Drain – Assessing the Role of Job Attributes and Individual Traits

Marco Bertoni
Debdeep Chattopadhyay
Yuanyuan Gu

JUNE 2023

Attributes and levels

Table 1: Job attributes and their levels

Attribute	Levels
Location	Italy Your favourite European foreign country
Annual net income (PPP adjusted)	€20.000 €30.000 €40.000 €50.000 €60.000 €75.000
Job security	2-year fixed term contract, non-renewable 2-year fixed term contract with 50% renewal probability Permanent job
Professional development opportunities	Limited opportunities for research and training Some opportunities for research and training Good opportunities for research and training
Working conditions	High workload with frequent overtime work and nightshifts Adequate workload with little overtime work and nightshifts
Match of skills with job content	Your skills are higher than required by the job Your skills are exactly matched to what is required by the job Some of your skills are lower than required by the job and need further development

A choice set

Imagine that you have just completed your preferred specialization course and are faced with the following job offers for hospital doctor positions in your specialization. Which would you choose: A, B, or neither of the two?

	Job A	Job B	Opt-Out
Professional development Opportunity	Good opportunities for further research and training	Limited opportunities for further research and training	
Income (PPP adjusted)	€40,000	€40,000	
Job security	Permanent position	2-year temporary contract with 50% chance of a permanent position afterward	
Working Conditions	High workload with frequent overtime work and night shifts	Adequate workload with little overtime work and night shifts	
Match of skills with job content	Your skills are exactly matched to what is required by the job	Some of your skills are lower than required by the job and need further development	
Country	Your favourite foreign European country	Italy	
Which would you choose?	○	○	○

Current DCE projects

Topic	Funders	Team members
Saving men 'under the radar' by understanding their preferences for suicide prevention service	MRFF	Anam Bilgrami, Noura Saba, Henry Cutler, et al
A priority-setting framework for value-based healthcare: Evidence from Australia	MRFF	Mona Aghdaee, Olukorede Abiona, Henry Cutler
Hearing and vision support design to improve quality of life for people living with dementia receiving home care services	MRFF	Piers Dawes, Sabrina Lenzen, Melinda Toomey (UQ)
Australians' preferences for mental healthcare services	ARC DP	Kompal Sinha, Lisa Magnani,Francesco Chirico, et al
Attraction and retention of workforce for the early childhood education and care sector	ACT Education Directorate	Sheila Degotardi, Jun Gu, Rebecca Mitchell, et al
EQ-5D with the hearing "bolt-on" items: developing a new quality of life measure for hearing impairment	Cochlear, MQ	Bonny Parkinson, Rajan Sharma, Henry Cutler, et al
Patient preferences for Knee Replacement Surgery in Australia	Johnson & Johnson Medical, MQ	Mutsa Gumbie (J&J), Henry Cutler, Kompal Sinha

DCE Design

How to construct DCE choice sets?

Step 1: attributes and levels

Products to choose are defined using attributes and their levels

- Attributes must be conceptually mutually exclusive

How to select attributes and levels?

- Literature view
- Focus groups
- Interviews

How many attributes and levels?

- Attributes: 3-7
- Levels: 2-8

Step 2: experimental design

A large number of combinations

- Three attributes, each with four levels: 4 x 4 x 4 = 64 possible products
- Experimental design needed to reduce the burden

Experimental design methods:

- Orthogonal design
- Efficiency design

Experimental design software:

- Ngene
- Sawtooth Software

Step 2: experimental design

Within a choice set

- 2~3 alternatives/options
- Forced choice: more efficient but may induce bias
- Unforced choice: opt-out, status quo

Too many choice sets generated:

- Blocking
- 8~16 choice sets per block
- e.g., 30 choice sets => 3 blocks with 10 choice sets each block

DCE data analysis

Multinomial choice models and beyond

Random utility theory

The utility gained from choosing product 1 for individual n: $U_{n1} = V_{n1} + \varepsilon_{n1}$

- V_{n1} is the systematic utility component
- ε_{n1} is the stochastic utility component

Decision makers maximise their utility through choices

- If $U_{n1} > U_{n2}$, the individual n will choose product 1 over product 2

We observe the choices, not the utilities. But based on the random utility theory, we may use statistical models to estimate the utility function given the choices.

The conditional logit

$$U_{i1} = \alpha_1 + \text{Income}_{i1}\beta + \text{Country}_{i1}\gamma + \varepsilon_{i1}$$
$$U_{i2} = \alpha_2 + \text{Income}_{i2}\beta + \text{Country}_{i2}\gamma + \varepsilon_{i2}$$
$$U_{i3} = \alpha_3 + \varepsilon_{i3}$$

- We estimate the utility function based on data and assumptions of the stochastic components
- Normal distribution => multinomial probit
- Gumbel distribution => multinomial/conditional logit
- Pr (choosing alt 1)

$= \exp(\alpha_1 + \text{Income}_{i1}\beta + \text{Country}_{i1}\gamma) / (\exp(\alpha_1 + \text{Income}_{i1}\beta + \text{Country}_{i1}\gamma) + \exp(\alpha_2 + \text{Income}_{i2}\beta + \text{Country}_{i2}\gamma) + \exp(\alpha_3))$

$= \exp(\alpha_1 - \alpha_3 + \text{Income}_{i1}\beta + \text{Country}_{i1}\gamma) / (\exp(\alpha_1 - \alpha_3 + \text{Income}_{i1}\beta + \text{Country}_{i1}\gamma) + \exp(\alpha_2 - \alpha_3 + \text{Income}_{i2}\beta + \text{Country}_{i2}\gamma) + 1)$

The mixed logit

- Conditional logit limitations:
  - Independence of Irrelevant Alternatives (IIA) assumption
  - Preference homogeneity

- Preference heterogeneity: random parameters $\alpha_{\iota}, \beta_{\iota}, \gamma_{\iota}$ – unobserved heterogeneity

- Which should be random?

- Which random distributions?

- Are they correlated?
  - MSL: cannot accommodate many
  - Bayesian: can accommodate full correlations – the prior for the covariance matrix needs to carefully chosen

Willingness to pay (WTP)

- WTP for country (to stay in Italy) = $\gamma_\iota / \beta_\iota$
- mean ($\gamma_\iota / \beta_\iota$) does NOT equal to mean (γ_ι)/mean of (β_ι)
- Easy way out: fixing the coefficient of income
- Simulation: draw a random sample from the distribution of γ_ι and β_ι and generate the empirical distribution of $\gamma_\iota / \beta_\iota$
- Extreme values: trim, median

Willingness to pay space

- $U = \beta_\iota (\alpha_\iota / \beta_\iota + \text{Income} + \text{Country}^* \gamma_\iota / \beta_\iota) + \varepsilon$
- $\beta_\iota \sim$ log-normal distribution
- WTP space: directly estimate $\gamma_\iota / \beta_\iota$

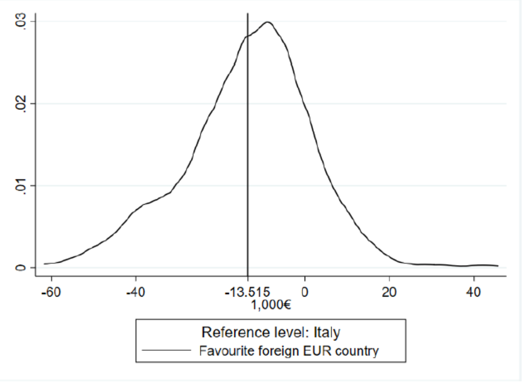
Train, K., & Weeks, M. (2005). Discrete choice models in preference space and willingness-to-pay space. In *Applications of simulation methods in environmental and resource economics* (pp. 1-16). Springer, Dordrecht.

The Medical Brain Drain Study

Table 4: Baseline WTP-space mixed logit estimates. Mean and SD.

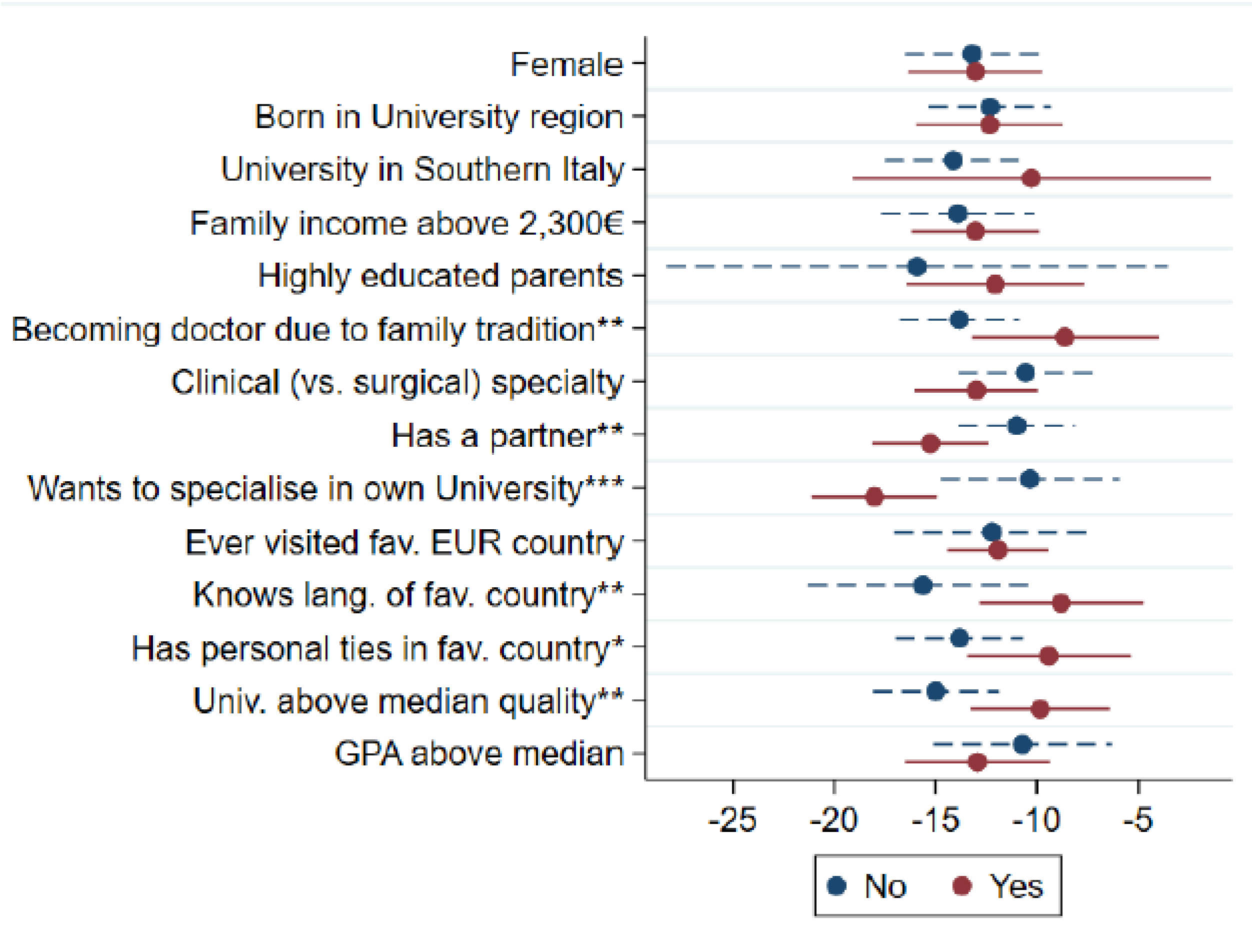
Variable	Mean	SD
Income (α_i)	0.126***	0.106***
	(0.009)	(0.008)
Job location WTP - reference: Italy		
Favourite foreign EUR country	-13,515***	17,216***
	(1,298)	(1,501)

Figure 1: WTP distribution for jobs located in respondents' favourite European country.



Notes: The vertical bar indicates the mean of the distribution.

Observed heterogeneity (interactions)



Challenges in modelling heterogeneity

- How to use individual characteristics to explain heterogeneity
  - Interactions
  - Regress the estimated WTP on individual characteristics
  - Latent class and then identify the profile for each class

- The mixing distribution may not be normal
  - Latent class logit
  - The mixed-mixed logit: a discrete mixture-of-normals heterogeneity distribution
  - Flexible mixing distribution

Train, K. (2016). Mixed logit with a flexible mixing distribution. *Journal of choice modelling*, *19*, 40-53.

- The correlations between preference parameters may not be trivial

Application of machine learning methods

- Learning Multinomial Logit (L-MNL) : divide the systematic part of the utility specification into (1) a knowledge-driven part, and (2) a data-driven one, which learns a new representation from available explanatory variables.

Sifringer, B., Lurkin, V., & Alahi, A. (2020). Enhancing discrete choice models with representation learning. *Transportation Research Part B: Methodological*, *140*, 236-261.

- Use machine learning techniques to discover the interaction between alternative attributes and individual characteristics

Han, Y., Pereira, F. C., Ben-Akiva, M., & Zegras, C. (2020). A neural-embedded choice model: Tastenet-mnl modeling taste heterogeneity with flexibility and interpretability. arXiv preprint arXiv:2002.00922.

- Gaussian process latent class choice models

Sfeir, G., Rodrigues, F., & Abou-Zeid, M. (2022). Gaussian process latent class choice models.

Transportation Research Part C: Emerging Technologies, *136,* 103552.

Thank you!

yuanyuan.gu@mq.edu.au

Please check MUCHE website for our projects and HDR program:

https://www.mq.edu.au/research/research-centres-groups-and-facilities/prosperous-economies/centres/centre-for-the-health-economy

Issues of DCEs

It is a survey and asks people to choose under hypothetical scenarios

- Poor quality data (not taken seriously, driven by money)
- Hypothetical bias (what they say differs from what they will do)
- Cognitively demanding (using heuristics)

Potential solutions:

- To ensure respondents are engaged with the survey (cheap talk, oath, incentives)
- To test quality (repeat test, dominant choice test)
- To avoid complex design (not too many attributes and choice sets)
- To accommodate uncertainty or other behaviours in econometric modelling (attribute non attendance)

Practical challenges

It can be very costly!

You need to learn and do many things:

- Literature review
- Focus group/interview
- Experimental design
- Survey design
- Data collection
- Econometric analysis

It takes much longer time than research using secondary data and can be risky

- Need to prepare for mistakes and failures
- Better work with experienced researchers first