NATIONAL ACADEMIES Sciences Engineering Medicine

TRB TRANSPORTATION RESEARCH BOARD

TRB Webinar: Design Strategies for Stated Choice Experiments

April 15, 2024

4:00 – 5:30 PM

PDH Certification Information

1.5 Professional Development Hours (PDH) – see follow-up email

You must attend the entire webinar.

Questions? Contact Andie Pitchford at TRBwebinar@nas.edu

The Transportation Research Board has met the standards and requirements of the Registered Continuing Education Program. Credit earned on completion of this program will be reported to RCEP at RCEP.net. A certificate of completion will be issued to each participant. As such, it does not include content that may be deemed or construed to be an approval or endorsement by the RCEP.

ENGINEERING RCEP REGISTERED CONTINUING EDUCATION PROGRAM

AICP Credit Information

1.5 American Institute of Certified Planners Certification Maintenance Credits

You must attend the entire webinar

Log into the American Planning Association website to claim your credits

Contact AICP, not TRB, with questions

Purpose Statement

This webinar will provide guidance in selecting suitable design properties and will address common design misconceptions. Presenters will discuss advanced choice experiment designs, where they can be employed, and how the implementation can be operationalized. Presenters will also share hands-on experiences from industry and academia to avoid common pitfalls.

Learning Objectives

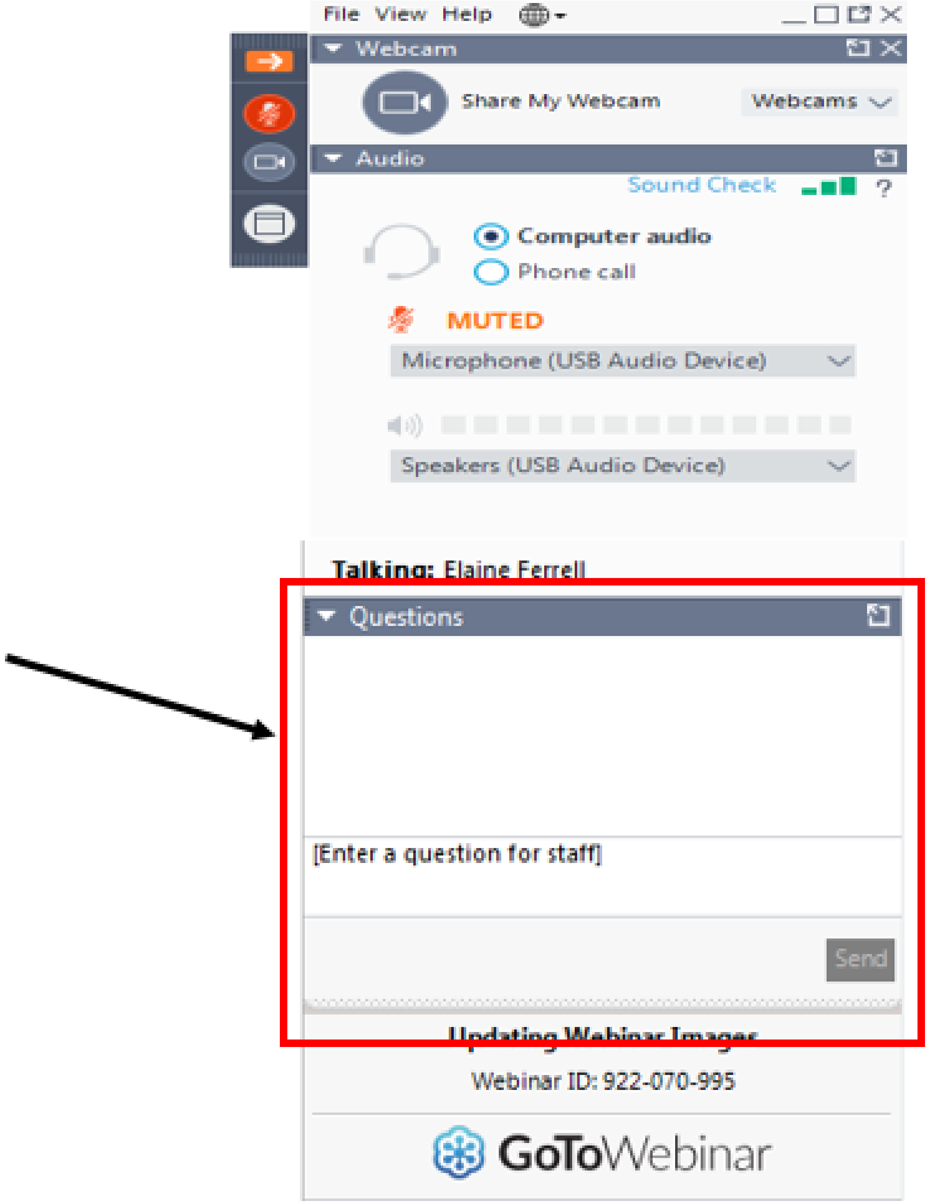
At the end of this webinar, you will be able to:

(1) Respond to common misconceptions in designing choice experiments

(2) Provide practical guidance on selecting suitable design properties for advanced choice experiments

Questions and Answers

- Please type your questions into your webinar control panel
- We will read your questions out loud, and answer as many as time allows



Today's Moderators

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decision modelling technology

NATIONAL ACADEMIES Sciences Engineering Medicine

Addressing misconceptions in stated choice experiment design

TRB Webinar

Design Strategies for Stated Choice Experiments

Prof Michiel Bliemer

Institute of Transport and Logistics Studies

THE UNIVERSITY OF SYDNEY

Outline

- Design considerations for choice experiments
- Design generation & choice task presentation
- Eight myths regarding choice experiments

Design considerations for choice experiments

Design considerations for choice experiments

Experimental design

- Matrix with attribute level combinations, where
  - Each column represents an attribute of an alternative
  - Each row represents a choice task

Bike	Bus A		bus B	
dist	$time_A$	$cost_A$	$time_B$	$cost_B$
10	10	1	20	3
2	20	2	30	1
5	30	3	10	2
5	10	2	20	1
5	20	3	30	2
5	30	1	10	3
5	10	2	20	1
5	20	1	10	2
10	30	3	30	3

Bike	Bus A	Bus B
5 km	20 min $3	30 min $2
○	○	○

Design considerations for choice experiments

Realism

- A good design contains realistic attribute level combinations
- Non-sensible attribute level combinations should be avoided

Bike	Bus A		Bus B	
dist	$time_A$	$cost_A$	$time_B$	$cost_B$
10	10	1	20	3
2	20	2	30	1
5	30	3	10	2
5	10	2	20	1
5	20	3	30	2
5	30	1	10	3
5	10	2	20	1
5	20	1	10	2
10	30	3	30	3

Unrealistic attribute level combinations

Design considerations for choice experiments

Balance

- A good design contains a high degree of attribute level balance
- Highly unbalanced designs should be avoided

Bike	Bus A		Bus B	
dist	$time_A$	$cost_A$	$time_B$	$cost_B$
10	10	1	20	3
2	20	2	30	1
5	30	3	10	2
5	10	2	20	1
5	20	3	30	2
5	30	1	10	3
5	10	2	20	1
5	20	1	10	2
10	30	3	30	3

Unbalanced attribute levels

Design considerations for choice experiments

Variety

- A good design contains a variety of attribute level combinations
- Repeated or similar choice tasks should be avoided

Bike	Bus A		Bus B	
dist	$time_A$	$cost_A$	$time_B$	$cost_B$
10	10	1	20	3
2	20	2	30	1
5	30	3	10	2
5	10	2	20	1
5	20	3	30	2
5	30	1	10	3
5	10	2	20	1
5	20	1	10	2
10	30	3	30	3

Repeated choice tasks

Design considerations for choice experiments

Trade-offs

- A good design allows trade-offs between attributes
- Choice tasks with dominant alternatives should be avoided

Bike	Bus A		Bus B	
dist	$time_A$	$cost_A$	$time_B$	$cost_B$
10	10	1	20	3
2	20	2	30	1
5	30	3	10	2
5	10	2	20	1
5	20	3	30	2
5	30	1	10	3
5	10	2	20	1
5	20	1	10	2
10	30	3	30	3

No trade-off

Design considerations for choice experiments

Trade-offs

- A good design allows trade-offs between attributes
- Choice tasks with dominant alternatives should be avoided

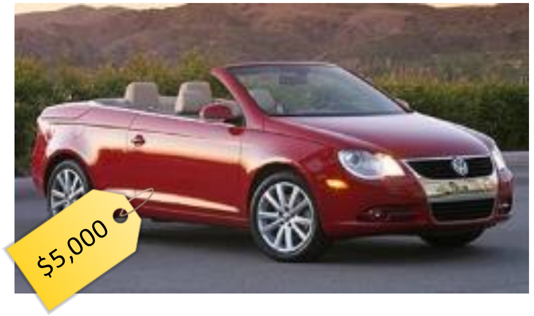
Bike	Bus A		Bus B	
dist	$time_A$	$cost_A$	$time_B$	$cost_B$
10	10	1	20	3
2	20	2	30	1
5	30	3	10	2
5	10	2	20	1
5	20	3	30	2
5	30	1	10	3
5	10	2	20	1
5	20	1	10	2
10	30	3	30	3

Bus B is dominant

Design considerations for choice experiments

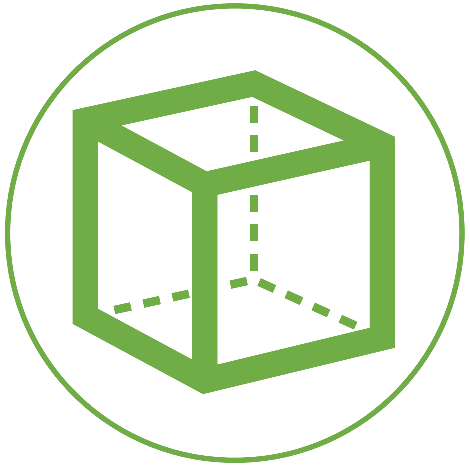
Dominant alternative

- Alternative that is best across all attributes
- Often present in unlabelled experiments
- Choice task with dominant alternative provides no information, and should be detected and avoided



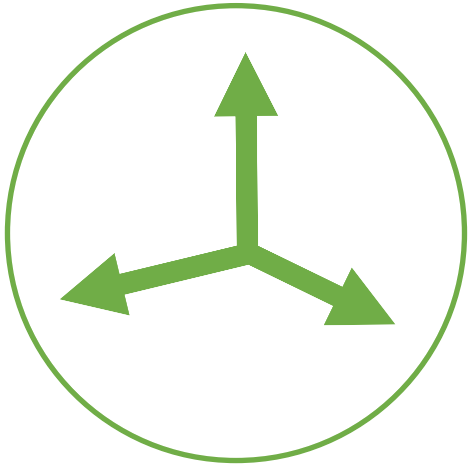
Design considerations for choice experiments

Design types

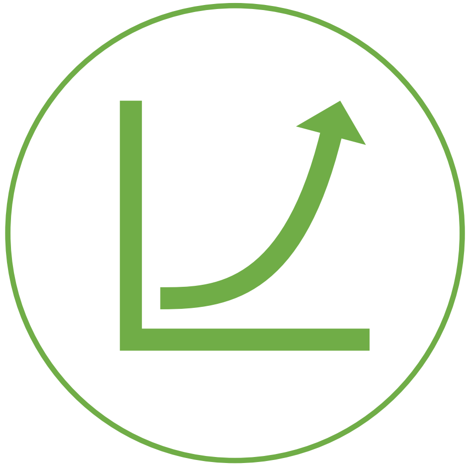


Full factorial design

Random design



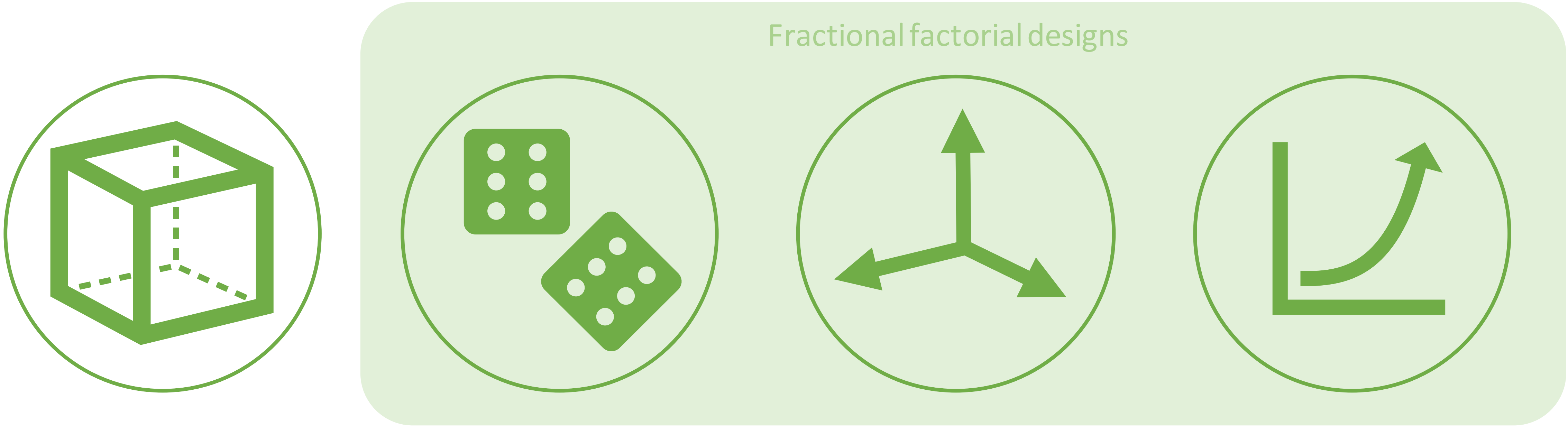
Orthogonal design



Efficient design

Design considerations for choice experiments

Design types



Full factorial design

all possible
attribute level combinations

Random design

random
attribute level combinations

Orthogonal design

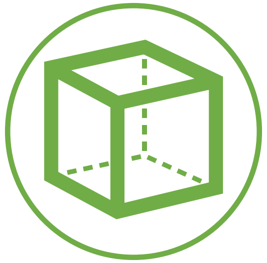
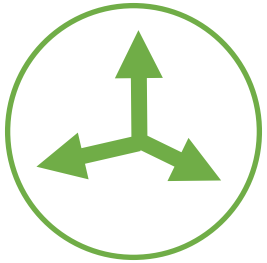
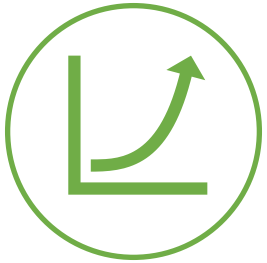
balanced
attribute level combinations

Efficient design

trade-off maximising
attribute level combinations

Design considerations for choice experiments

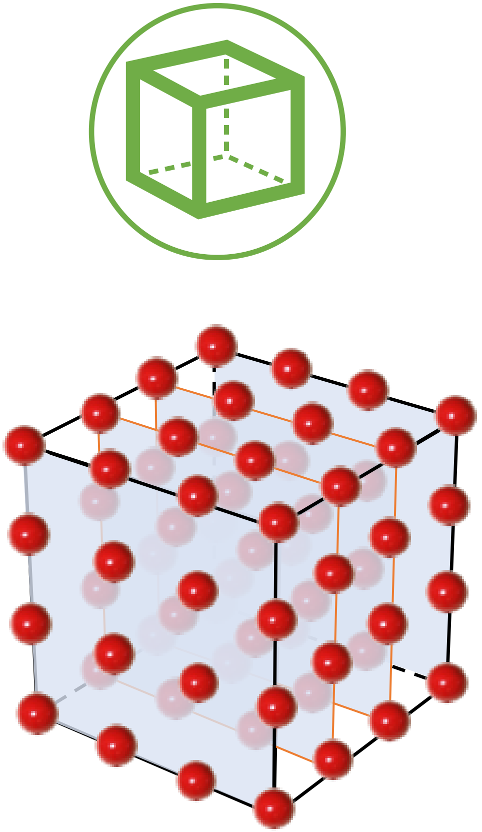
Design types – strengths and weaknesses

	Full factorial	Random	Orthogonal	Efficient
				
Realism	●○○	●●●	●○○	●●●
Trade-offs	●○○	●○○	●●○	●●●
Balance	●●●	●○○	●●●	●●○
Variety	●●●	●●●	●●○	●●○

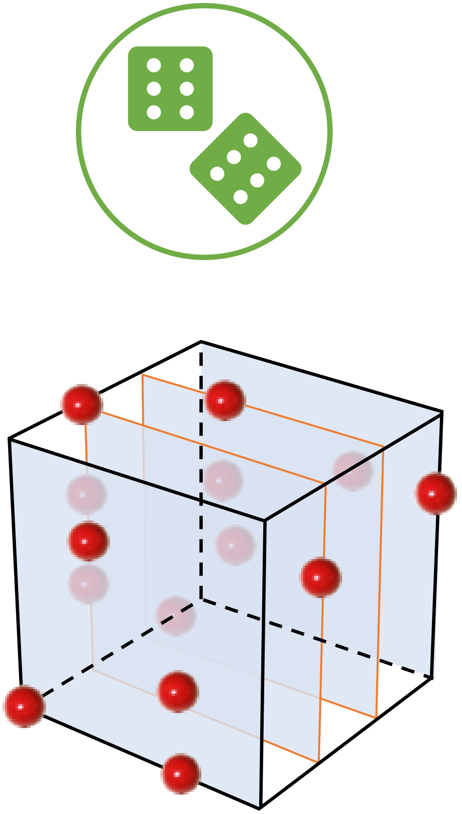
Design considerations for choice experiments

Design types – different attribute level combinations

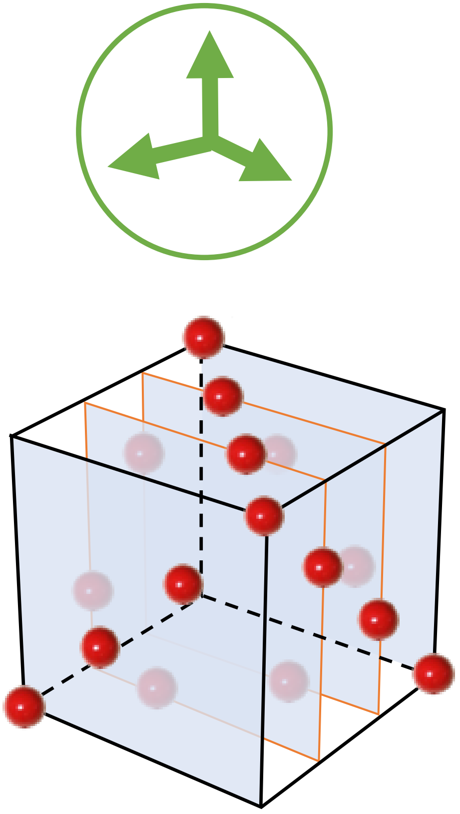
Full factorial



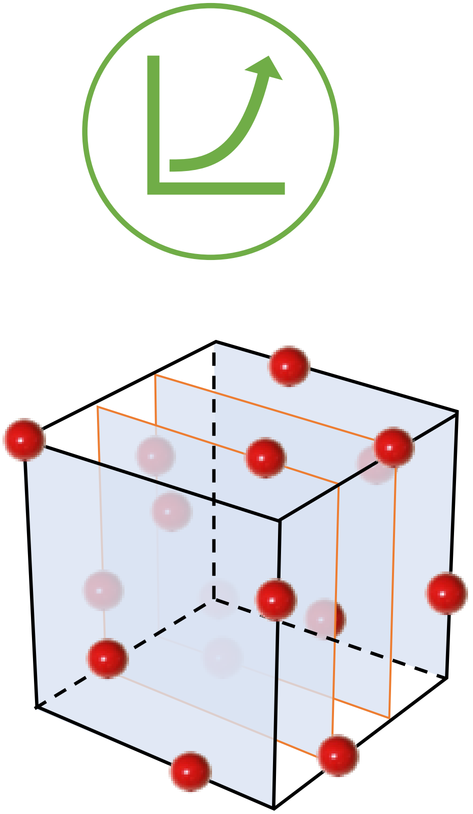
Random



Orthogonal



Efficient



Design generation & choice task presentation

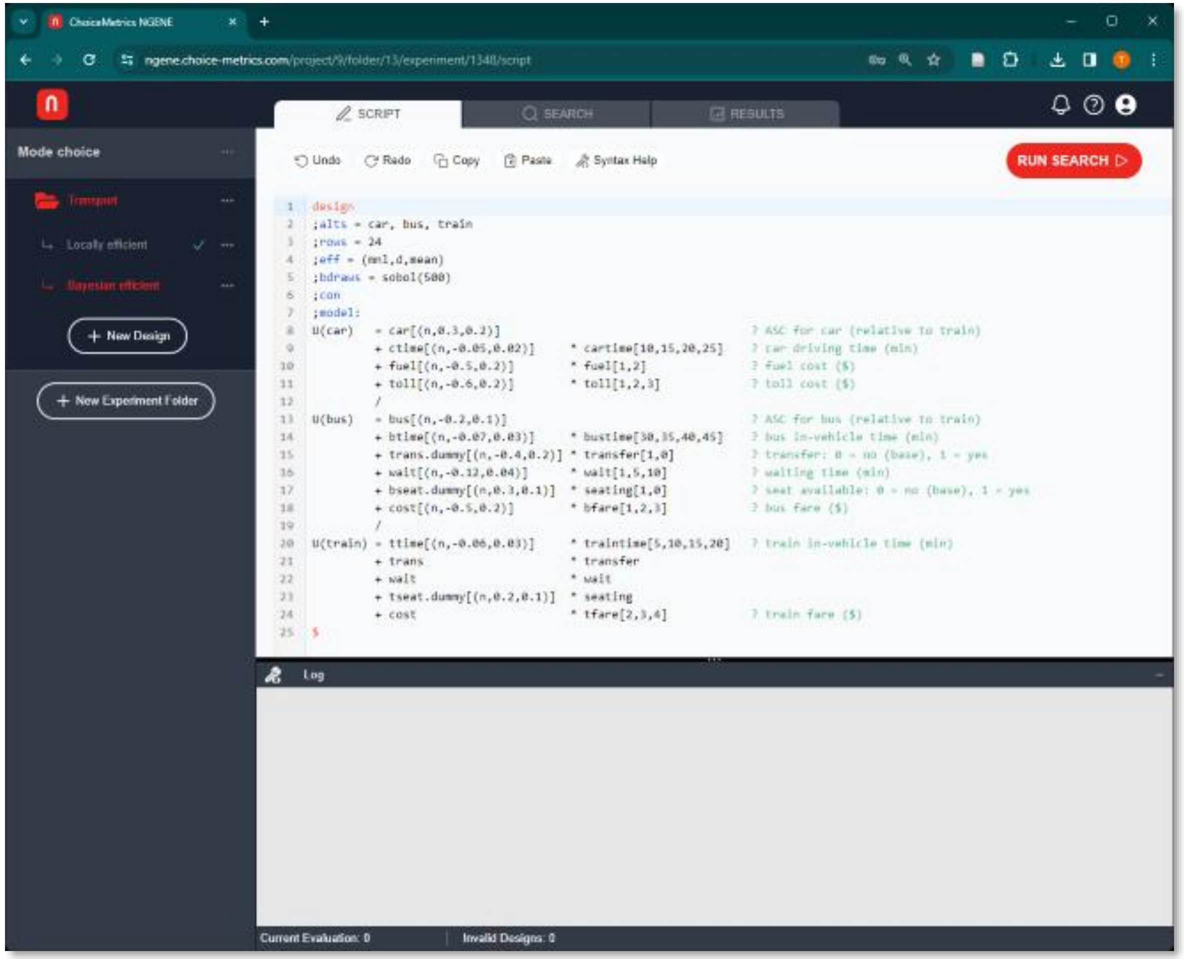
Design generation & choice task presentation

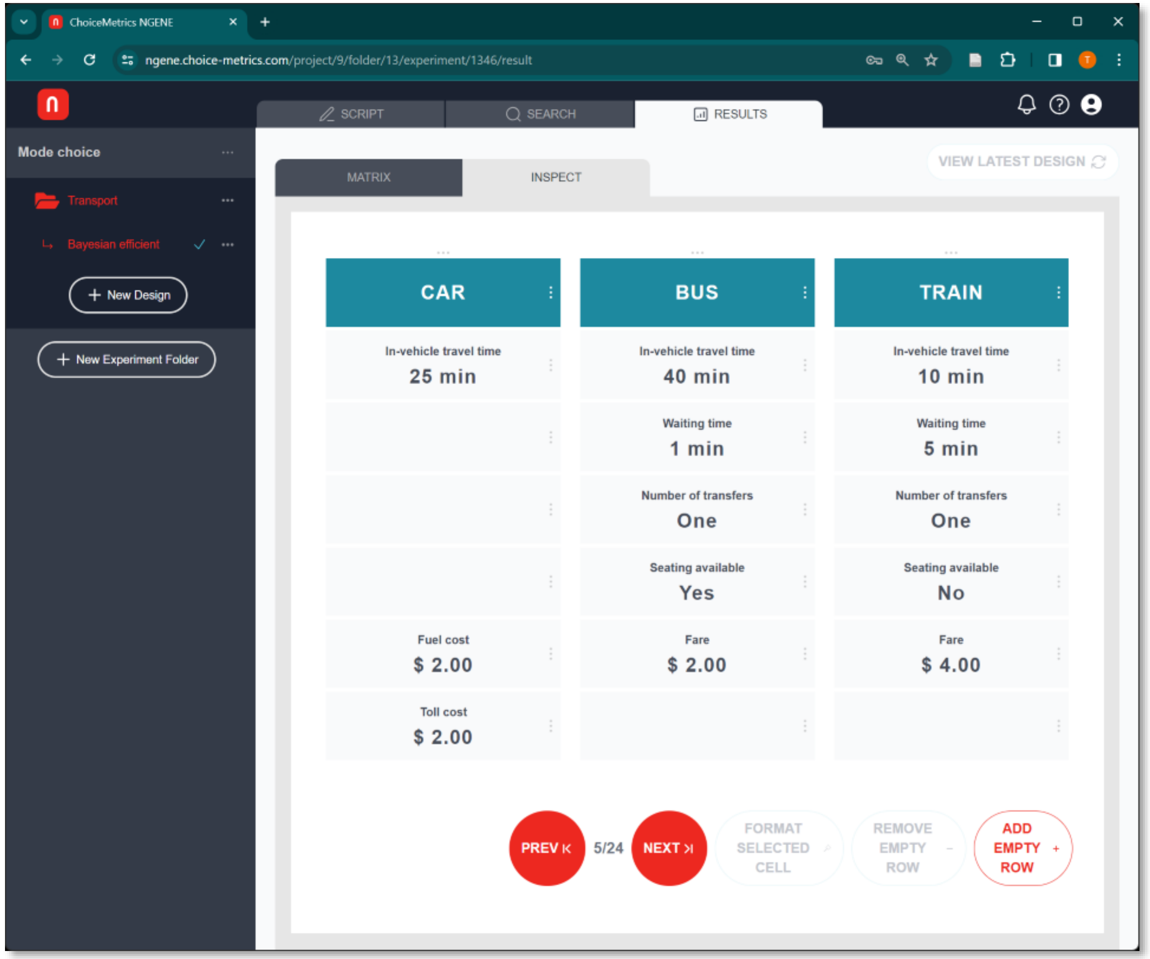
Design generation tools

	Full factorial	Random	Orthogonal	Efficient
❑ Spreadsheet	■	■		□
❑ Design library			■	
❑ Design software	■	■	■	■

Design generation & choice task presentation

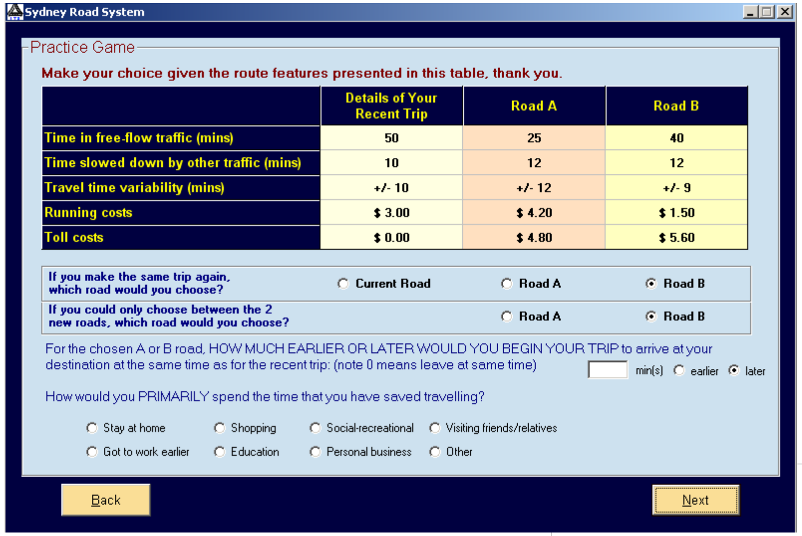
Example – Bayesian efficient design generation in Ngene





Design generation & choice task presentation

Choice task presentation



Sydney Road System

Practice Game

Make your choice given the route features presented in this table, thank you.

	Details of Your Recent Trip	Road A	Road B
Time in free-flow traffic (mins)	50	25	40
Time slowed down by other traffic (mins)	10	12	12
Travel time variability (mins)	+/- 10	+/- 12	+/- 9
Running costs	$ 3.00	$ 4.20	$ 1.50
Toll costs	$ 0.00	$ 4.80	$ 5.60

If you make the same trip again, which road would you choose?	Current Road	Road A	Road B
If you could only choose between the 2 new roads, which road would you choose?		Road A	Road B

For the chosen A or B road, HOW MUCH EARLIER OR LATER WOULD YOU BEGIN YOUR TRIP to arrive at your destination at the same time as for the recent trip: (note 0 means leave at same time) min(s) earlier later

How would you PRIMARILY spend the time that you have saved travelling?

Stay at home | Shopping | Social-recreational | Visiting friends/relatives
Got to work earlier | Education | Personal business | Other

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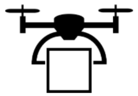
Hensher and Rose (2006)

	Drone	Locker	Postie
			
Speed	2 business days	3 business days	5 business days
Delivery method	Leave in a safe place	Secure in locker	Leave at front door
Time window	9am - 5pm (30 minutes)	24/7 (kept for two days)	6pm - 9pm (no choice)
Cost	$2	$6	$8
Which would you choose?			

Merkert et al. (2022)

Lockshin et al. (2010)

Myth 1

"An experimental design that is not orthogonal results in biased parameters"

Myth 1

“An experimental design that is not orthogonal results in biased parameters”

- All design types (orthogonal, efficient, random) can result in unbiased parameters
- Revealed preference data is also not orthogonal

- An orthogonal design in linear regression has as benefit that parameters can be estimated independently, but in choice modelling no such benefit exists
  - This includes both main effects and interaction effects

Myth 1

"An experimental design that is not orthogonal results in biased parameters"

- Orthogonal designs can introduce biases
  - Cannot avoid dominant alternatives
  - Cannot avoid unrealistic choice tasks

Flight I	Flight II	Flight III
Economy class	Business class	Economy class
Sandwich	No meal	Warm meal
35" seat pitch	32" seat pitch	28" seat pitch
8 hours flight time	10 hours flight time	12 hours flight time
2 transfers	Direct	1 transfer
$1600	$1200	$800

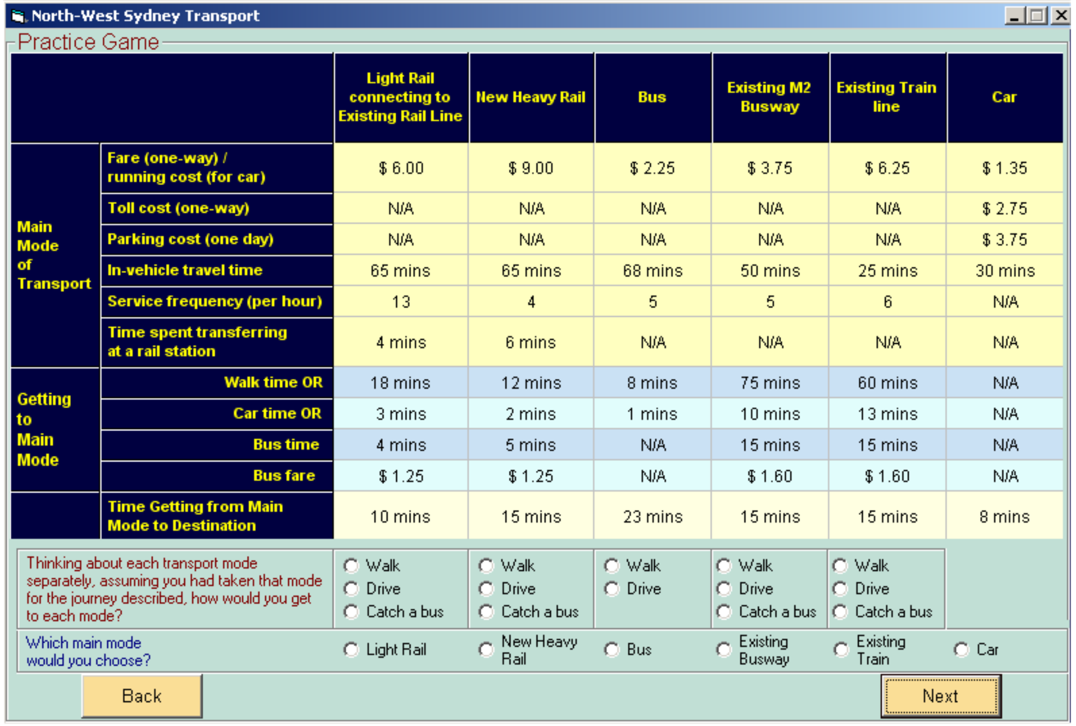
Myth 2

“Choice experiments can only include a small number of alternatives and attributes”

Myth 2

“Choice experiments can only include a small number of alternatives and attributes”

- Showing all alternatives/attributes in each choice task could lead to a high cognitive burden, but should we exclude relevant alternatives and attributes?



North-West Sydney Transport

Practice Game

		Light Rail connecting to Existing Rail Line	New Heavy Rail	Bus	Existing M2 Busway	Existing Train line	Car
Main Mode of Transport	Fare (one-way) / running cost (for car)	$ 6.00	$ 9.00	$ 2.25	$ 3.75	$ 6.25	$ 1.35
	Toll cost (one-way)	N/A	N/A	N/A	N/A	N/A	$ 2.75
	Parking cost (one day)	N/A	N/A	N/A	N/A	N/A	$ 3.75
	In-vehicle travel time	65 mins	65 mins	68 mins	50 mins	25 mins	30 mins
	Service frequency (per hour)	13	4	5	5	6	N/A
	Time spent transferring at a rail station	4 mins	6 mins	N/A	N/A	N/A	N/A
Getting to Main Mode	Walk time OR	18 mins	12 mins	8 mins	75 mins	60 mins	N/A
	Car time OR	3 mins	2 mins	1 mins	10 mins	13 mins	N/A
	Bus time	4 mins	5 mins	N/A	15 mins	15 mins	N/A
	Bus fare	$ 1.25	$ 1.25	N/A	$ 1.60	$ 1.60	N/A
	Time Getting from Main Mode to Destination	10 mins	15 mins	23 mins	15 mins	15 mins	8 mins
Thinking about each transport mode separately, assuming you had taken that mode for the journey described, how would you get to each mode?		Walk / Drive / Catch a bus	Walk / Drive / Catch a bus	Walk / Drive	Walk / Drive / Catch a bus	Walk / Drive / Catch a bus	
Which main mode would you choose?		Light Rail	New Heavy Rail	Bus	Existing Busway	Existing Train	Car

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Next

Hensher and Rose (2007)

Myth 2

"Choice experiments can only include a small number of alternatives and attributes"

- One could consider a partial choice set design if the number of alternatives is large

Which means of transport would you prefer when travelling to work?

Car	Tram	Bus	Train	Metro	Bike	Walk
	20 min $2 1 transfer		10 min $1 1 transfer	15 min $2 0 transfers	40 min	
	○		○	○	○	

Myth 3

"Choice experiments can only include a small number of alternatives and attributes"

- One could consider a partial profile design if the number of attributes is large

Which hotel for a business trip do you prefer?

Hotel A	Hotel B
$200	$100
*****	***
300 m from city	300 m from city
Free wifi	No wifi
Breakfast included	Breakfast included
Swimming pool	No swimming pool
No gym	No gym

Myth 3

"Only revealed preference data should be used because stated preference data suffers from hypothetical bias"

Myth 3

“Only RP data should be used because SP data suffers from hypothetical bias”

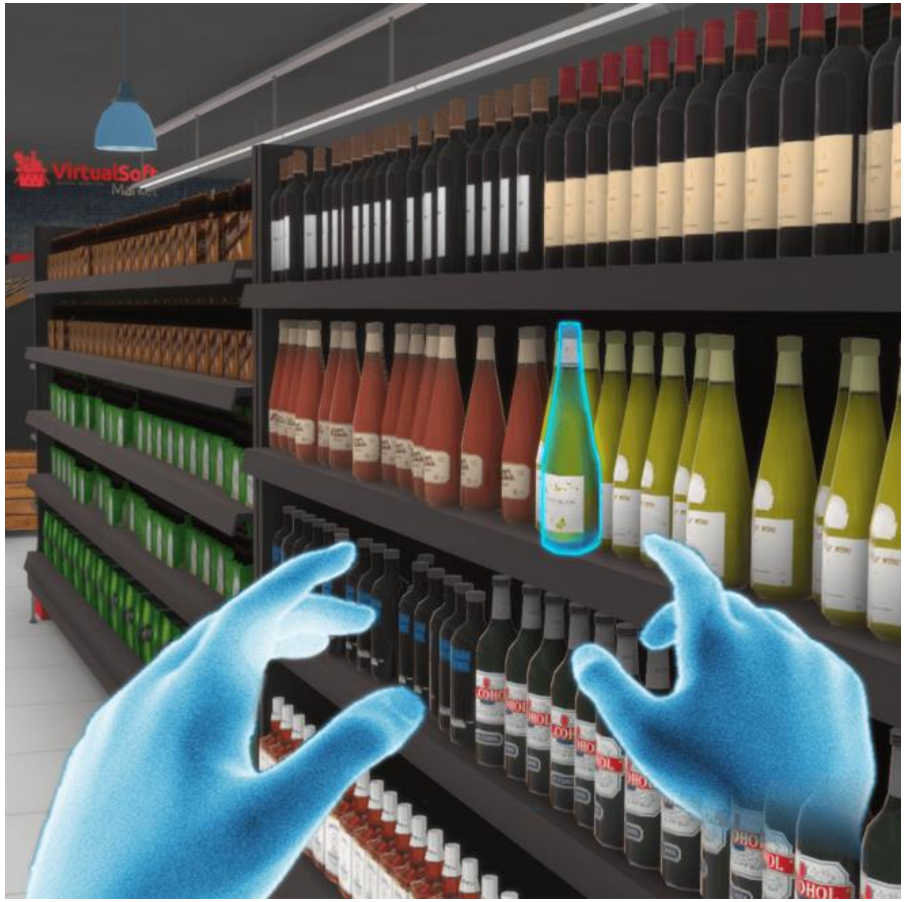
- There exist mitigation strategies to reduce hypothetical bias
  - Incentive compatibility
  - Cheap talk
  - Solemn oath
  - Honesty priming
  - Certainty scale calibration
  - Consequentiality scripts
  - Time-to-think
  - Induced truth telling and Bayesian truth serum
  - Budget reminders
  - Realistic framing
  - Referencing and pivoting

Myth 3

"Only RP data should be used because SP data suffers from hypothetical bias"

- Virtual reality experiments

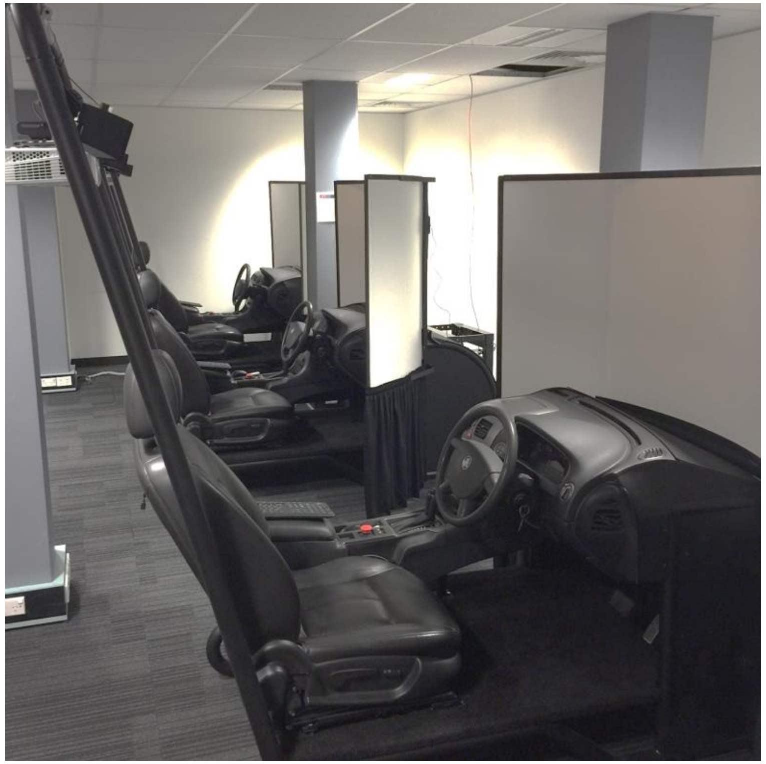
Mokas et al. (2021)

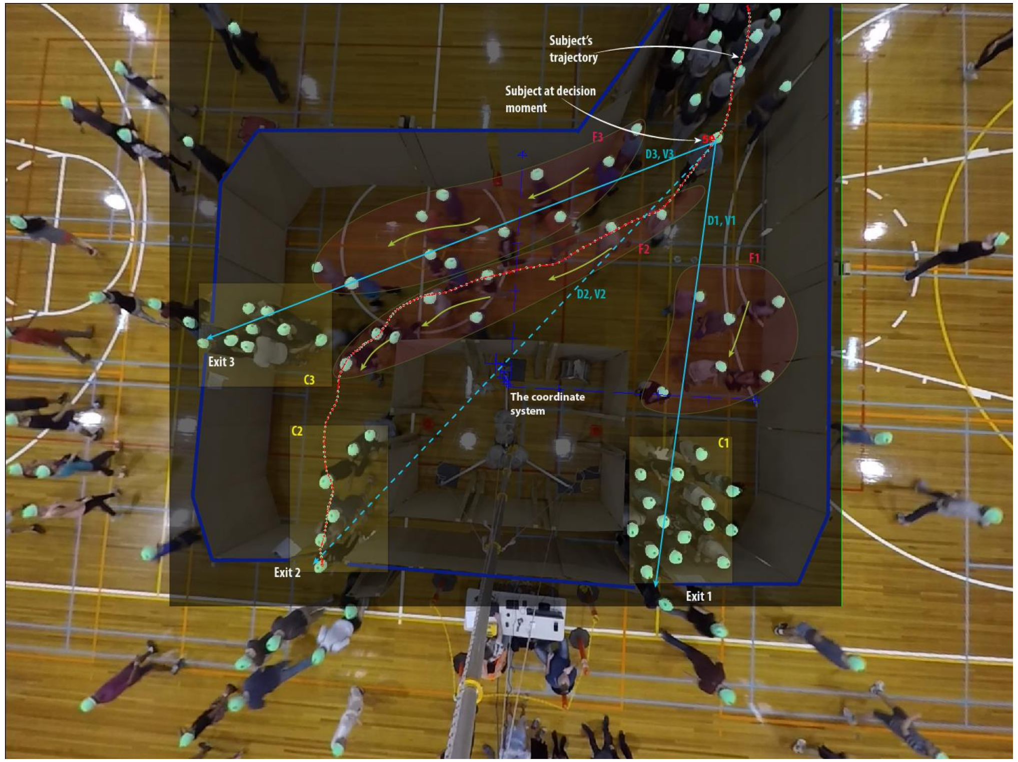


Myth 3

"Only RP data should be used because SP data suffers from hypothetical bias"

- Laboratory experiments





Haghani et al. (2020)

Myth 3

“Only RP data should be used because SP data suffers from hypothetical bias”

hypothetical / laboratory

- non-consequential choice experiments
- (partially) consequential choice experiments

non-hypothetical / non-laboratory

- quasi-revealed / lab-in-the-field choice experiments
- self-reported choice observations in the field
- naturalistic choice observations

more realistic →

← more control

Myth 3

"Only RP data should be used because SP data suffers from hypothetical bias"

- Attribute levels can be pivoted about self-reported reference levels to make choice task more familiar

Current	Route A	Route B
30 min. free-flow	24 min. free-flow	27 min. free-flow
10 min. congested	9 min. congested	15 min. congested
$2 toll cost	$3 toll cost	$1 toll cost

Current			Route A			Route B		
free-flow	congested	toll cost	free-flow	congested	toll cost	free-flow	congested	toll cost
REF	REF	REF	REF - 20%	REF - 10%	REF + 1	REF - 10%	REF + 50%	REF - 1
REF	REF	REF	REF + 20%	REF - 20%	REF - 2	REF + 20%	REF - 40%	REF + 2
REF	REF	REF	REF + 10%	REF + 10%	REF + 2	REF + 10%	REF - 10%	REF + 1
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Myth 3

"Only RP data should be used because SP data suffers from hypothetical bias"

- RP data is great, but also has issues
  - Cannot be used to analyse alternatives or attributes that do not yet exist
  - Often requires a subjective process of determining characteristics of non-chosen alternatives that can introduce other biases
  - Preferences towards attributes cannot be measured if their levels do not vary much in reality
  - Correlations across attributes may make it impossible to disentangle choice behaviour
  - Self-reported behaviour can be biased (social desirability) or incomplete

Myth 4

"Only revealed preference data should be used because choice experiments suffer from design artefacts"

Myth 4

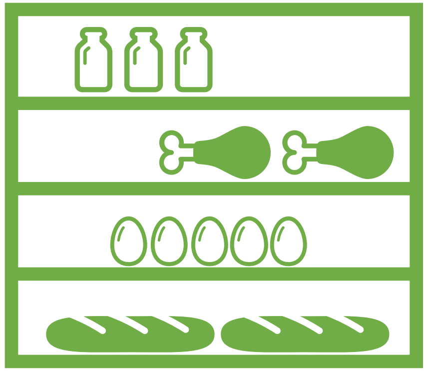
“Only RP data should be used because choice experiments suffer from design artefacts”

- There exist mitigation strategies to reduce design artefacts
  - Systematically randomise the order of alternatives
  - Systematically randomise the order of attributes
  - Systematically randomise the order of choice tasks
  - Multiple ways to frame attributes
  - Multiple choice contexts

Myth 4

"Only RP data should be used because choice experiments suffer from design artefacts"

- RP data is great, but also has issues
  - Behaviour often confounded with (single fixed) presentation order
  - Behaviour often confounded with (single fixed) framing of attributes
  - Behaviour often confounded with (single fixed) prevailing choice context



Myth 5

"Showing random combinations of attribute levels in choice tasks is a bad idea"

Myth 5

“Showing random combinations of attribute levels in choice tasks is a bad idea”

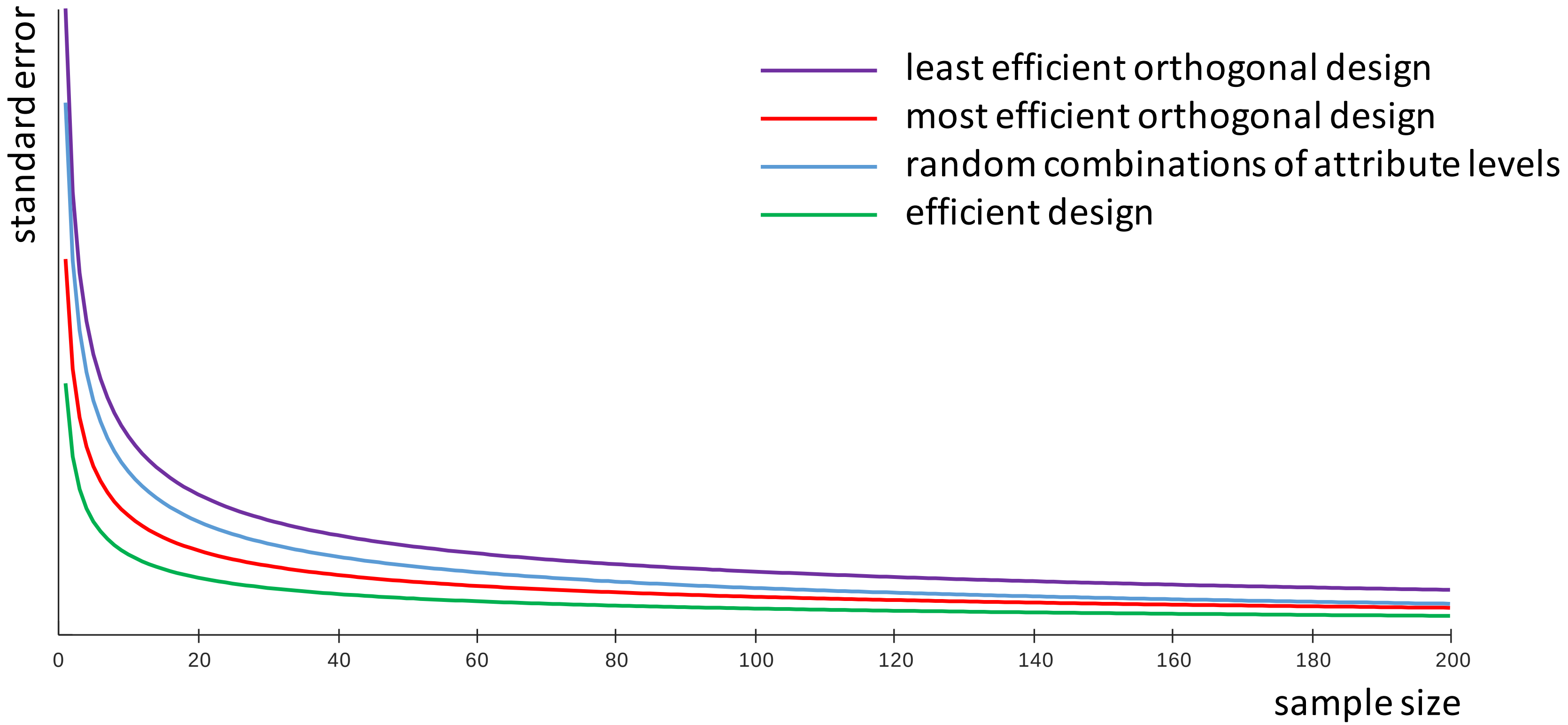
- If sample size is large, random combinations of attribute levels work fine
- Could still impose constraints/prohibitions if needed

- Efficient designs are preferred for small sample sizes

Myth 5

"Showing random combinations of attribute levels in choice tasks is a bad idea"

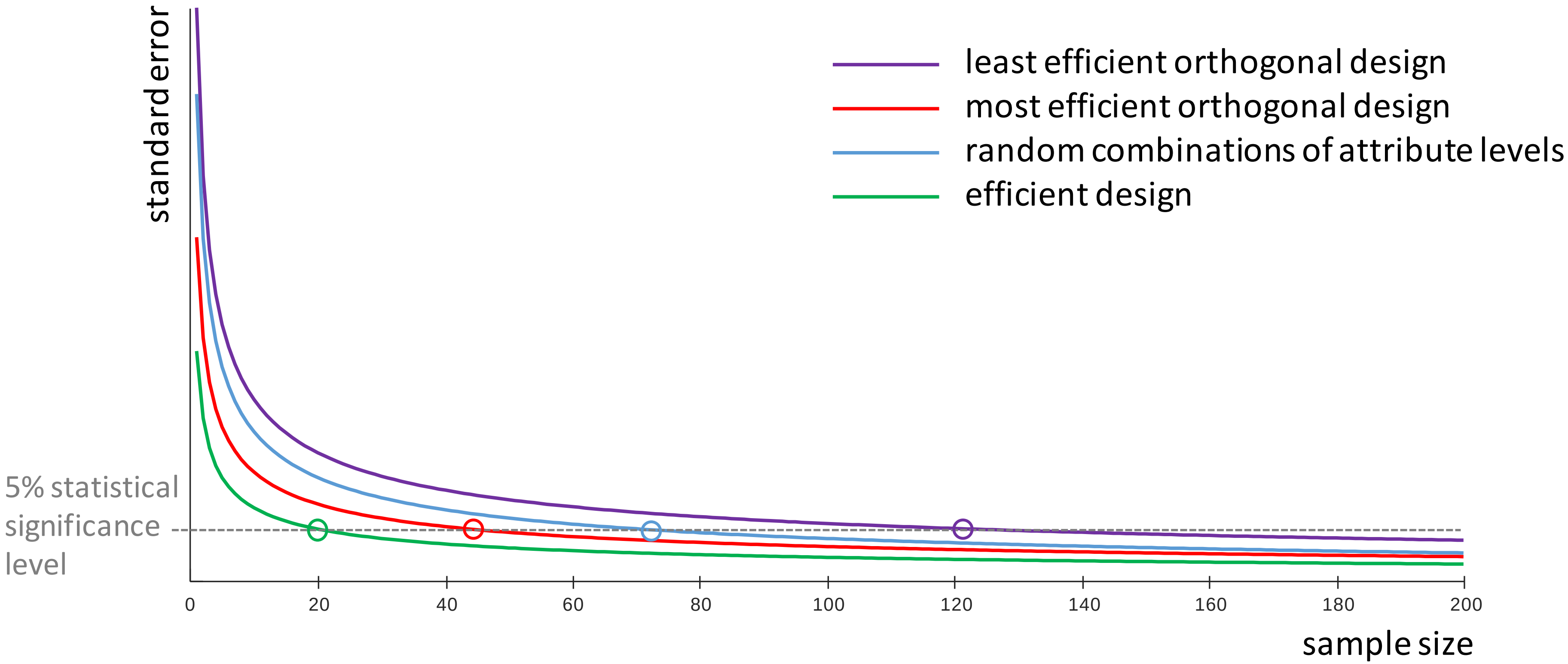
- Variation in data assists in reducing standard errors



Myth 5

"Showing random combinations of attribute levels in choice tasks is a bad idea"

- Minimum sample size requirements



Myth 6

"The models assumed in the design and estimation phase should be the same"

Myth 6

“The models assumed in the design and estimation phase should be the same”

- The model assumed during the efficient design generation phase often deviates from the final model that is estimated
- Deviation generally does not cause estimation issues if the design size is sufficiently large, although it results in some data collection efficiency loss

‘Design’ model

- Multinomial logit
- Linear utility functions
- Main effects only
- Zero parameter priors

Efficiency loss

‘Estimation’ model

- Mixed logit
- Nonlinear utility functions
- Main and interaction effects
- Non-zero parameter estimates

Myth 7

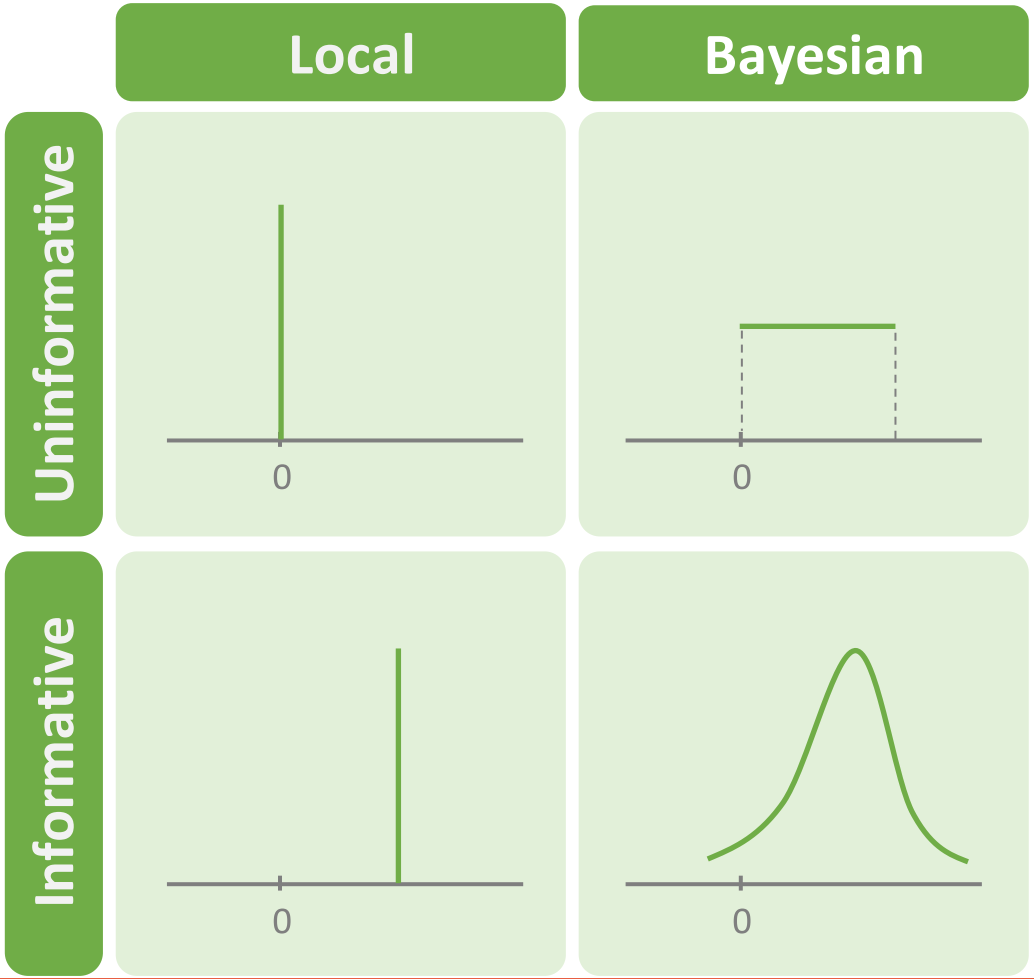
“Generating efficient designs is difficult because parameter priors are often not available”

Myth 7

"Generating efficient designs is difficult because parameter priors are often not available"

- Priors are best guesses of parameter values

- Priors can be obtained from a pilot study
- If no information is available, assume (near) zero priors



Myth 8

“Design efficiency can be compared across models”

Myth 8

"Design efficiency can be compared across models"

- *D*-errors (or *A*-errors) can only be compared within a model, not across models
  - Design II is more efficient than Design I for estimating Model A
  - Designs II and III have the same *D*-error. Design II is efficient for estimating Model A, but Design III is not efficient for estimating Model B

Recommendations

Recommendations

- Formulate utility functions prior to data collection
  - Informs the experimental design
  - Check identifiability of model
  - Distinguish scenario variables from attributes
- Re-think the use of orthogonal designs
  - They are restrictive and have little benefit
  - They often result in dominant alternatives or unrealistic profiles
- Use efficient designs when sample size is small
  - Preferably using Bayesian priors from a pilot study
  - Apply constraints/prohibitions to ensure realistic profiles
- Tailor choice tasks to individual decision-makers
  - Customised choice contexts, choice sets, and attribute levels
  - Reduces hypothetical bias

THANK YOU

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Courses in Choice Experiments & Modelling

***Sydney** 24-28 June 2024*
www.sydney.edu.au/business/our-research/institute-of-transport-and-logistics-studies/courses/discrete-choice-analysis.html

***Online** September-October 2024*
www.choicemodelling.academy

***Leeds** 4-8 November 2024*
cmc.leeds.ac.uk/courses-phds/cpd

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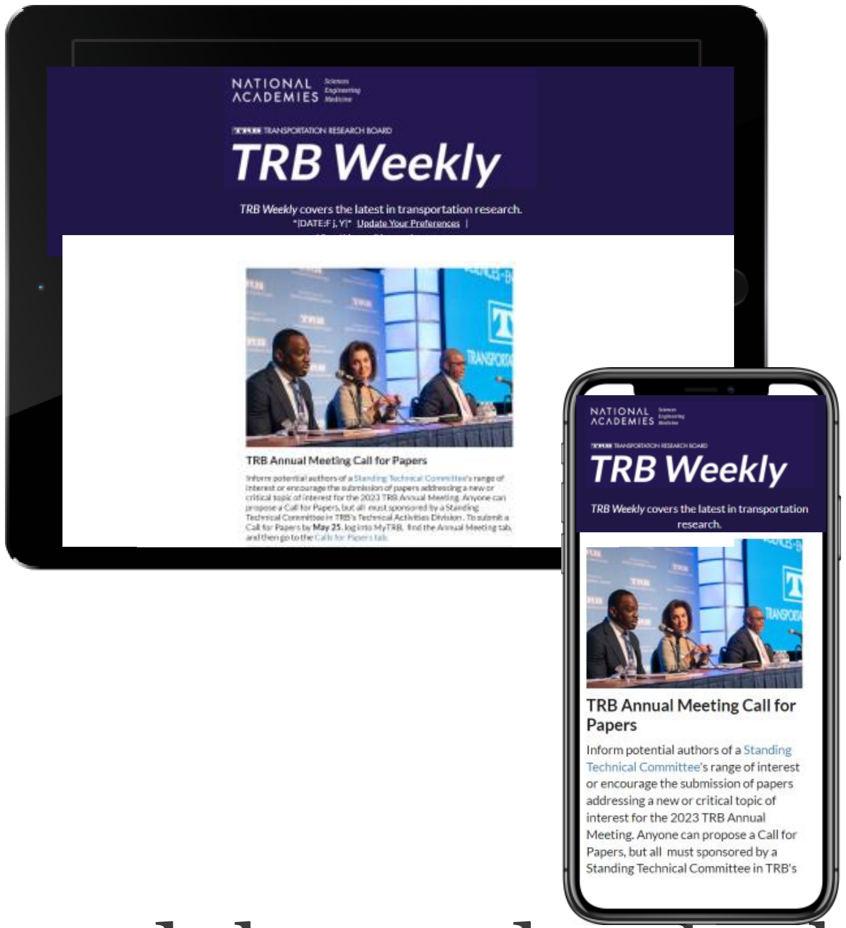

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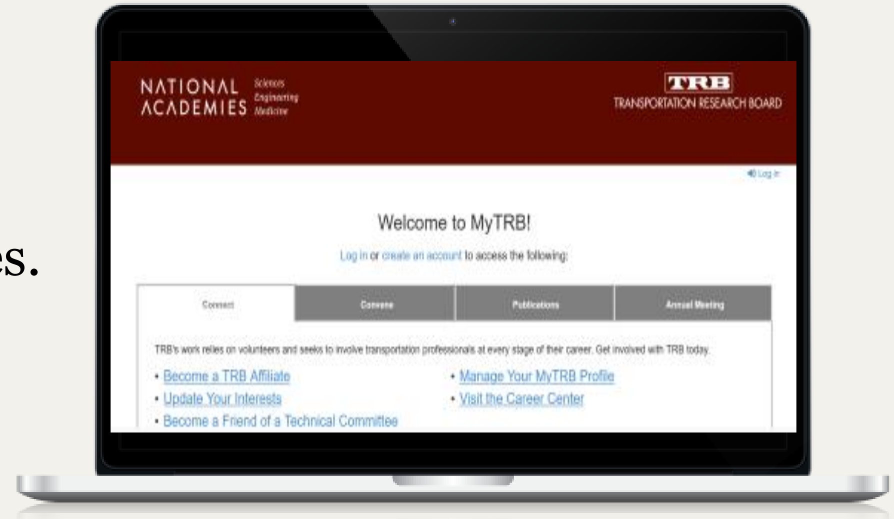

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