INTERNATIONAL SOCIETY FOR PHARMACOECONOMICS AND OUTCOMES RESEARCH
ISPOR NEW ZEALAND CHAPTER

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HEALTH TECHNOLOGY ASSESSMENT

REPORT OF ISPOR (NZ) Seminar, 18 April 2018, Auckland City Hospital

In this first issue for 2018, we report on the health technology assessment (HTA) focused seminar which ISPOR (NZ) hosted alongside its April 18, 2018 AGM, held at Auckland City Hospital.

This seminar included four presentations on the use of HTA in New Zealand practice and the measurement of patient preferences, critical for HTA use to improve population health. It highlighted the depth and range of research, data collation and other activity taking place in New Zealand to inform application of HTA.

In this issue we summarise two of the four presentations, from Professor Nick Wilson and Professor Carlo Marra. We will provide a summary of the following two contributions in our next issue:

Professor Stephen Munn presented on the activities of the Northern Region Clinical Practice Committee (NRCPC). This hospital-based HTA unit informs decisions to invest in new health technologies or disinvest/restrict access to existing health technologies. Stephen summarised decisions about health technology and advice given during NRCPC's 13-year lifetime, providing examples of real-world, post-implementation outcomes. He also reported on eligibility creep and its implications for actual versus ideal cost-utility.

Carsten Schousboe presented on his PhD research with the University of Otago to assess the most appropriate HR-QoL instrument for PHARMAC to use in economic appraisals. Different QOL instruments, each with different descriptive systems and valuation techniques, lead to differences in the values generated and risks of important effects being missed. No gold-standard method exists for choosing the most suitable approach, yet consensus is that one must be chosen.

ONLINE INTERACTIVE LEAGUE TABLES: QALYS, COSTS AND COST-EFFECTIVENESS

Nick Wilson is Professor of public health and co-director of the Burden of Disease Epidemiology, Equity and Cost-Effectiveness Programme (BODE^3) research programme at the University of Otago, Wellington. He reviewed the objectives of BODE^3 and shared the current status of the online interactive league table.

HRC-funded BODE^3 work has objectives related to dietary and physical activity interventions, interventions targeted by absolute cardiovascular disease (CVD) risk and morbidity and productivity in the aging population. It also comprises platform work including development and augmentation of the core model, epidemiology and cost data, and the extension of league tables to include productivity costs, benefit receipt, etc.

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Other funded work includes work on physiotherapy for arthritis and the Ministry of Business, Innovation and Employment programme covering rapid evaluations of dietary counselling, abdominal aortic aneurysm screening, diabetes mellitus self-help, mass media/Quitline, mobile applications and CVD dual medications.

BODE^3 collates the results of cost-effectiveness studies for multiple interventions into an interactive league table that can be used to sort and rank interventions by health gains (QALYs), costs, or cost-effectiveness (ICER).

Nick reviewed the available tabular and graphic comparisons of QALYs, costs and ICERs that are available in cancer prevention and control, tobacco control interventions, dietary sodium reduction and falls prevention in the current online interactive BODE^3 League Table (available at: https://nzcms-ct-data-explorer.shinyapps.io/trimleaguetable2/ with explanations in the blog series: *Public Health Expert* blog).

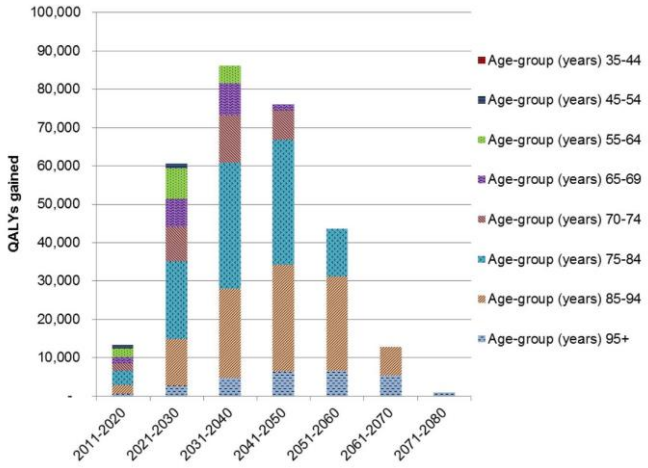

Figure 1: Who gains the QALYS and when (sodium reduction)

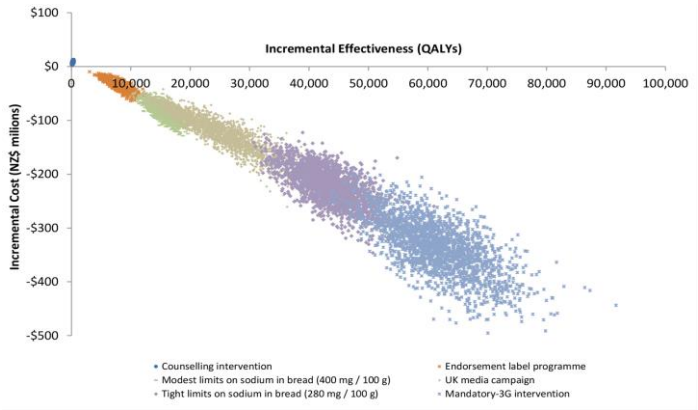

Figure 2: Example of cost-effectiveness plane (sodium reduction)

The ability to select for heterogeneity allows review of findings in specific population groups, for example, by age, gender or ethnicity (Figure 1).

Another option is to create cost-effectiveness planes for selective interventions, although only a simplified version is currently available in the online tool. A more detailed example from a published paper is shown in Figure 2.

While the tool can assist in in prioritising interventions, there are other considerations beyond health gain, cost-savings and cost-effectiveness. Using salt reduction intervention as an example, Nick noted the need to consider such factors as equity (eg, greater per capita gain for Māori) and the technical feasibility and political feasibility of optional interventions (eg, a salt tax would be controversial).

The BODE^3 Programme will continue to expand New Zealand interventions and the recently introduced Australian cost-utility analyses.

Other BODE^3 developments include online tools for the sector, a scholarly blog for knowledge translation and cost-benefit analysis work using the Treasury CBAx tool (eg, work on New Zealand border closure for severe pandemics).

Nick concluded by noting that the online interactive league table has a growing number of comparable methodologically comparative New Zealand interventions. However, there is still a lack of clarity as to the extent that it is informing decision-making by New Zealand policy-makers.

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OVERVIEW OF PREFERENCE BASED STUDIES USING EXAMPLES

Professor Carlo Marra is Dean of the School of Pharmacy at the University of Otago. He researches health outcomes, including assessment of quality of life, preferences, and cost effectiveness analyses.

Carlo reviewed choice experiments which are increasingly used in health services research for eliciting preferences in the absence of revealed preference data. The method involves asking individuals to choose a preferred specification of the good or service being evaluated with the goal of quantifying the utility (benefit) associated with different attribute levels describing the good or service (such as route of administration, side effects, clinic visits required, etc).

Responses to a range of choice sets are used to mathematically tease out preferences for different attributes.

An example of a discrete choice experiment (DCE) set is shown in Figure 3.

Treatment Features	Treatment A	Treatment B	Neither
Length of treatment	**12 months** of 1 pill daily	**9 months** of 1 pill daily	No Treatment
Frequency of clinic visit	**Every 2 weeks**	**Every 2 months**	None
Risk of developing active TB after treatment (benefit)	**0 out of 100 (0%)**	**4 out of 100 (4%)**	**10 out of 100 (10%)**
Chance of developing liver damage (side effect)	**1 out of 100 (1%)**	**5 out of 100 (5%)**	0 out of 100 (0%)
Chance of developing skin rash (side effect)	**0 out of 100 (0%)**	**10 out of 100 (10%)**	0 out of 100 (0%)
Chance of developing fatigue (side effect)	**5 out of 100 (5%)**	**0 out of 100 (0%)**	0 out of 100 (0%)
Which would you choose? **(tick only one box)**	Prefer Treatment A ☐	Prefer Treatment B ☐	Prefer No Treatment ☐

Guo N, Marra CA, et al. Value Health. 2011 Sep-Oct;14(6):937-43

Figure 3: Example of a DCE choice set for prophylactic TB treatment

The best worse scaling (BWS) approach gathers responses to sets of attributes that identify the best/most preferred and the worst/least preferred feature of each set which can then be modelled to get to utility values (see example in Figure 4).

Select the best (most preferred) feature and the worst (least preferred) feature of tuberculosis screening from the options provided.

Best (most preferred)		Worst (least preferred)
☐	Location: in another community	☐
☐	Test done by a registered nurse	☐
☐	Wait time: none	☐
☐	Test done by an allied health worker	☐
☐	Cost: R300	☐

O'Hara N, ..., Marra CA. PLoS One. 2015 Jul 21;10(7):e0133304

Figure 4: Sample BWS choice set for tuberculosis screening in gradating nurses

The underlying statistical models often used to analyse DCE data, such as multinomial logistic models, are highly mathematical and non-intuitive, effectively black box models. More complex methods such as mixed logit, heteroscedastic conditional logit and latent class analysis (non/semi parametric) are needed to account for heterogeneity but provide an even greater level of "black box" or non-intuitive findings.

In contrast, best-minus-worst scores used to analyse BWS are easy to understand, avert the "black box" scenario,

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and provide a good representation of preferences (linearly related to the mixed logit estimates of the conditional logit model in virtually every empirical study to date).

Carlo then presented three examples of discrete choice experiments, each using different methodologies.

The first example used best-worst survey design to establish preferences of the general population, parents and healthcare professionals in stratifying and targeting paediatric medulloblastoma, considering trade-offs between treatment intensity and survival including test characteristics, functional outcomes, psychological outcomes and economic burden.

Best-worst estimated parameters in intermediate prognosis showed, for example, that parents were more willing than clinicians to trade off disability (for parents, mild disability is more favourable than 70% survival rate whereas the opposite was found for clinicians).

The calculation of best-worst count score (equal to the difference between "times selected best" and "times selected worst", divided by total number of times) showed that quality of life has the biggest impact on clinicians' decision-making for patients with good prognosis and that severe, partial and mild disability are the least favourable attributes, respectively (Table 1).

	Good Prognosis Attributes	Best – Worst Score	Intermediate Prognosis Attributes	Best – Worst Score	Poor Prognosis Attributes	Best – Worst Score
Test Accuracy	100%	25.8%	100%	47.5%	100%	53.9%
	95%	9.1%	95%	37.5%	95%	45.8%
	90%	-11.0%	90%	5.7%	90%	15.2%
	85%	-25.6%	85%	-9.0%	85%	-0.2%
Quality of Life	Normal life	33.9%	Normal life	51.0%	Normal life	56.4%
	Mild disability	-42.3%	Mild disability	-12.3%	Mild disability	-2.9%
	Partial disability	-64.5%	Partial disability	-36.1%	Partial disability	-18.4%
	Severe disability	-74.1%	Severe disability	-63.5%	Severe disability	-49.6%
Survival Rate	100%	76.2%	85%	51.5%	55%	16.1%
	95%	64.1%	70%	15.1%	40%	-12.4%
	90%	21.0%	55%	-38.0%	25%	-50.6%
	80%	-13.0%	40%	-49.2%	10%	-53.8%

Khakban A, Mohammadi T, …Marra CA. Pediatric Blood & Cancer, 64(6), e26340. doi: 10.1002/pbc.26340

Table 1: Best-Worst count score for clinicians' preferences

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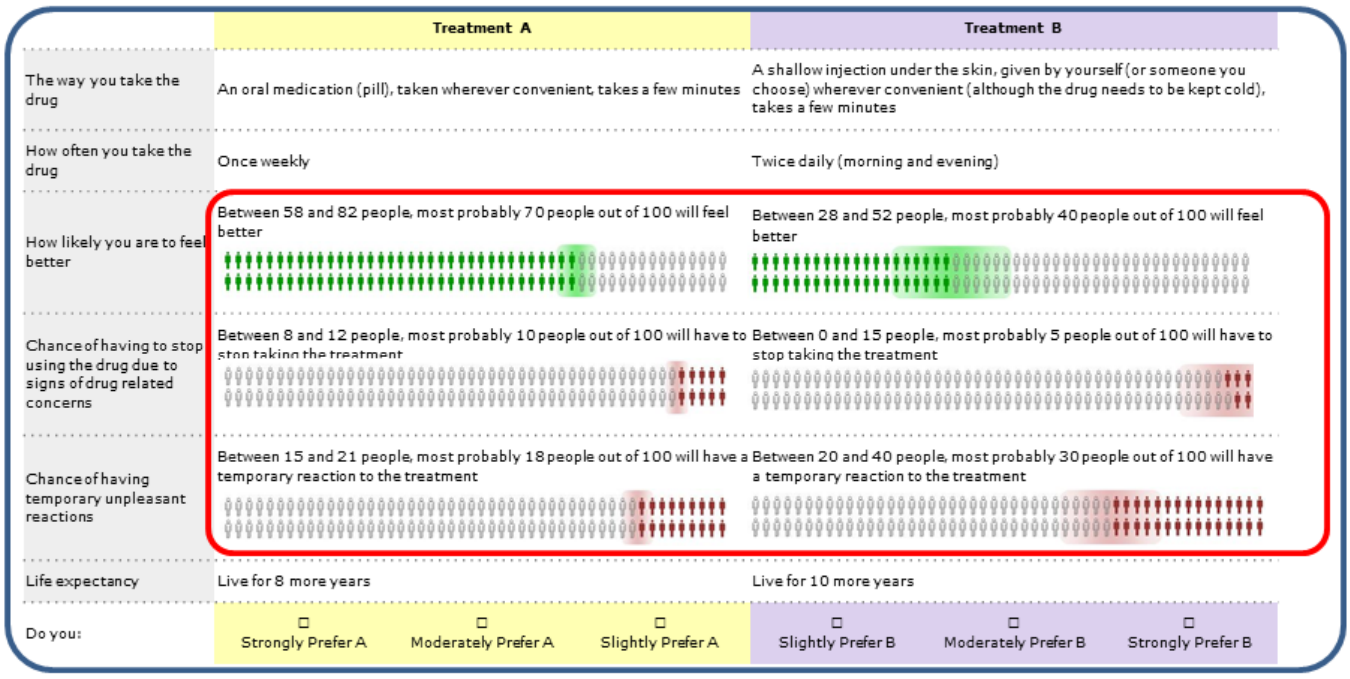
Carlo highlighted that best-minus-worst scores have the advantage of being easy, with simple calculations, but do not meet the economist definition of a trade-off and cannot be used alone to produce QALYs.

The second example used a DCE to describe how two methods for conveying imprecision in risk influence people's treatment decisions. Imprecision is rarely communicated in information regarding treatment benefits and harms yet is typically greater for newer treatments which have less quantity and fewer years of data.

An online survey including hypothetical questions about treatments for rheumatoid arthritis varied in the way imprecision was described, giving no imprecision or either a qualitative or quantitative description of imprecision (latter shown in Figure 5 using confidence intervals and a visual prop).



Bansback N, Harrison M, Marra CA. Med Decis Making 2015 Aug 24. pii: 0272989X15600708. [Epub ahead of print]

Figure 5: Survey giving quantitative description of imprecision

Analysis of imprecision using a conditional logit model was able to show:

- People value treatments more if they have greater precision in benefit and harm estimates that is conveyed qualitatively
- People do not value treatments more if they have greater precision which is conveyed quantitatively (with confidence intervals and a visual prop)
- Both qualitative and quantitative methods lead to small but significant increases in ambiguity aversion
- Reduced certainty attenuates demand for treatments based on 'newness' even in an identified group of 'early adopters' whose preference for treatment is influenced by newness, even where there are similar treatment effects (the so-called 'me-toos').

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The third example used latent class analysis in a DCE to determine consumers' food allergen labelling preferences and willingness to spend on improved labelling. The study used 18 choice-sets per respondent, each including two hypothetical alternatives (see example in Figure 6) along with two fixed tasks (based on qualitative data including children, allergy status and details).

Three distinct groups with different need and preferences for food labelling were identified. For example, those with a need for allergen avoidance had stronger preferences. A small proportion of respondents appeared indifferent to food allergen labelling.

Overall, there were preferences for precautionary and safety statements and symbols (and the use of symbols more than statements) and for little or no increase in cost for improved food allergen labelling.

Please imagine The Shortbread Company makes packaged shortbread. The ingredients of the shortbread are listed on the package. The ingredients are: wheat flour, butter, sugar, salt. In addition to listing the ingredients, the shortbread company wants to provide allergen information on the package. Below is a description of two different options for allergen labeling. After considering the two options for allergen labeling, please click the button under the option you prefer:

Features	Option 1	Option 2
Precautionary Statement	Contains wheat, diary, peanuts and treenuts	Not suitable for consumers with allergies to peanuts or treenuts
Safety Statement	Does not contain soy, eggs, fish, or shellfish	Not included
Use of Symbols	Precautionary	No symbols
Placement of Information	Package Front	Package Front AND Next to Ingredients
I would choose:	☐	☐

Figure 6: Example of a DCE choice set for food labelling preferences

Carlo closed by noting that choice experiments in health, although they have limitations, can give quantitative preferences and reveal how people purport to trade off attributes. Latent class analysis can be useful to investigate preference heterogeneity. Such understanding can inform policies and uptake of various services.

NEWSLETTER ANNOUNCEMENT FROM UNIVERSITY OF YORK – CENTRE FOR HEALTH ECONOMICS

Welcome to CHE's first newsletter of 2018, Issue 31. In this issue we report on some of our recently completed research projects and related activities, including:

- The measurement of socioeconomic inequalities in the duration of untreated psychosis
- Methodological issues in the economic evaluation of social care
- The economics of precision medicine

We also report on a new project examining the health and health system consequences of conflict in Columbia, as well as details of an article on mental health quality that appeared in the top 10 list of the British Journal of General Practice in 2017.

Recent publications, staff activities and new projects are also listed.

I hope you find the newsletter interesting. If you would like to find out more about any of the articles in the newsletter do contact us on che-news@york.ac.uk

Professor Maria Goddard, Director