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# Cognitive overload? An Exploration of the Potential Impact of Cognitive Functioning in Discrete Choice Experiments with Older People in Health Care.

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#### ABSTRACT

**Objectives:** This exploratory study sought to investigate the impact of cognitive functioning on the consistency of individual responses to a DCE study conducted exclusively with older people.

**Methods:** A DCE to investigate preferences for multidisciplinary rehabilitation was administered to a consenting sample of older patients (aged 65 years and over) following surgery to repair a fractured hip (N=84). Conditional logit, mixed logit, heteroscedastic conditional logit and generalised multinomial logit regression models were utilised to analyse the DCE data and to explore the relationship between the level of cognitive functioning (specifically the absence or presence of mild cognitive impairment as assessed by the minimental state, MMSE) with preference and scale heterogeneity.

**Results:** Both the heteroscedastic conditional logit and generalised multinomial logit models indicated that the presence of mild cognitive impairment did not impact significantly upon the consistency of the responses to the DCE.

**Conclusions:** This study provides important preliminary evidence relating to the impact of mild cognitive impairment upon DCE responses for older people. It is important that further research is conducted in larger samples and more diverse populations to further substantiate the findings from this exploratory study and to assess the practicality and validity of the DCE approach with populations of older people.

#### Introduction

There has been an exponential increase in the number of DCE studies undertaken within health care during the last two decades since the first seminal paper by Propper and colleagues to assess the disutility of time spent on NHS waiting lists [1]. However, despite the increase in their proliferation, DCE studies specifically designed for and conducted with older people remain relatively rare in comparison with those conducted and reported upon with general adult samples. Given future patterns of socio-demographic change and the aging of the population it is reasonable to expect that the development of DCE studies designed specifically for application with older people are likely to increase markedly during the coming decades. The reliability of DCE responses from older people with varying levels of cognition and the threshold level of cognitive ability required for an older person to reliably complete a DCE are therefore highly important but currently under-researched areas of investigation. This exploratory study sought to investigate this issue empirically by assessing the potential impact of cognitive functioning upon DCE generated responses from a sample of older people recovering from hip fracture. Specifically we employed mixed logit, heteroskedastic conditional logit and generalised multinomial logit regression models to more formally investigate the potential for preference and scale heterogeneity in responses for the total sample and by sub-groups classified according to the absence or existence of mild cognitive impairment.

#### Methods

#### Questionnaire design and administration

A DCE questionnaire was developed for administration with a population of older people recovering from surgery to repair a fractured hip. The design and administration of the DCE questionnaire is discussed in detail in a separate paper [2]. The DCE comprised four salient attributes relating to rehabilitation therapy following hip fracture including levels of pain and effort endured, the risk of further falls and injury from participating in rehabilitation therapy

and the level of mobility achieved. Following approval granted from the relevant research ethics committee, participants for the DCE were recruited from two hospitals in Adelaide, South Australia, sequentially over an 18 month period between May 2009 and November 2010. Patients were approached for participation if they had been admitted to hospital with a falls related proximal femur fracture, were 60 years old or above, and were not currently receiving palliative care.

Cognitive functioning was assessed by the Mini-Mental State Examination (MMSE), a routinely administered brief instrument for the measurement of global cognitive function [3]. The MMSE was developed in 1975 and has since proven to be valid and reliable across a variety of clinical, epidemiological, and community survey studies [4]. MMSE scores were categorized according to the three group categorization criteria adopted by Tombaugh and McIntyre's seminal review whereby a score of 17 or below indicates severe cognitive impairment, a score of 18 to 23 indicates mild cognitive impairment and a score of 24 or above indicates no cognitive impairment [4]. For patients classified with severe cognitive impairment informed consent was sought from a proxy family member who was also asked to complete the DCE questionnaire on behalf of the patient and from the patient's perspective.

The DCE questionnaire was administered using an interviewer mode of administration, post-operatively at approximately one to two weeks following surgery to repair the fractured hip. In advance of the main study, the DCE questionnaire was piloted with a small sample of patients (N=10) with a range of levels of cognitive function to check respondents understanding of the questions and to indicate that they were providing meaningful responses. The findings from the pilot study indicated that patients with mild cognitive impairment (MMSE 19-23) were able to fully complete the questionnaire and were also able to provide meaningful responses. Minor changes to question layout and phraseology were made as a consequence of the findings of the pilot study to improve participant understanding.

#### Data analysis

The data from the DCE were analysed within the framework of random utility theory which assumes that respondents choose the alternative that maximizes their utility. Let  $U_{itj}$  be the utility individual *i* derives from choosing alternative *j* in choice scenario *t*. Utility is given by:

$$U_{itj} = x'_{itj}\beta_i + \varepsilon_{itj}$$

where  $x_{itj}$  is a vector of observed attributes of alternative *j*,  $\beta_i$  is a vector of individual specific coefficients reflecting the desirability of the attributes, and  $\varepsilon_{itj}$  is a stochastic term. For a traditional linear-index model (i.e.,  $x'_{itj}\beta_i$ ), the probability of respondent *i* choosing alternative *j* in choice situation *t* can be specified as:

$$\Pr(choice_{it} = j \mid \beta_i) = \frac{\exp(\sigma_i x'_{itj} \beta_i)}{\sum_{k=1}^{J} \exp(\sigma_i x'_{itk} \beta_i)}$$

where  $\sigma_i$  is an individual specific scale of the idiosyncratic error, which is inversely proportional to the error variance. Effects coding was utilised for the analysis of the DCE data. Four key econometric model specifications were applied ranging in their respective levels of model sophistication. (1) the simple conditional logit (which is unable to take account of either preference of scale heterogenity), (2) the heteroskedastic conditional logit (HCL, which can take account of scale heterogeneity), (3) the mixed logit (accounting for taste or preference heterogeneity) and (4) the advanced generalised multinomial logit (G-MNL, which takes account of both preference and scale heterogeneity simultaneously) [5-9].

Within this data-set it is reasonable to hypothesize that participants in the lower cognitive functioning sub-group may make choices that are considerably less consistent (or with a larger error variance) than those in the higher cognitive functioning sub-group. A heteroscedastic conditional logit model was employed to test whether error variances differed according to lower or higher cognitive functioning [6-8]. In order to account for taste or preference heterogeneity a mixed logit model was employed, by specifying  $\beta_i$  to follow a distribution of which the mean and standard deviation are estimated [9]. Finally, the recently

operationalized G-MNL model which can accommodate both preference and scale heterogeneity in a single model was employed [10]. Information criterion are commonly utilised to choose the overall fit of DCE models with the Bayesian Information Criterion (BIC) being increasingly utilised as the preferred measure [11]. All econometric analyses were conducted in Stata version 12.1 (StataCorp LP, College Station, Texas, USA) using clogit, clogithet [12], mixlogit [13], and gmnl [14] commands.

Comparisons between choice models that have been generated from two groups of respondents, , need to take account of differences in unobserved variability (i.e., scale), between the data sources [15]. For example, a comparison between a sample of patients with higher levels of cognitive functioning and a sample of patients with lower levels of cognitive functioning and a sample of patients with lower levels of cognitive functioning and a sample to take account of scale differences. The Swait and Louviere test was used to formally test for such differences across the two sub-samples [16].

#### Results

A total of 149 patients who had recently undergone surgery to repair a hip fracture were approached of whom 87 (58%) consented to participate in the study and 84 (56%) fully completed all of the DCE questions (74 patients and 10 proxy family members). Table 1 presents a summary of the characteristics of the participants. For the self-completing participants, the majority N=52 (70%) were women and the mean age was 80 years of age. Whilst a small proportion, N=10 (14%) were living in residential care prior to fracture, the vast majority were living independently in the community prior to admission, N=64 (86%). The majority of self-completing participants (68%) were classified with normal cognitive function and were born in Australia (73%). In addition the vast majority (84%) indicated that they found the DCE task either 'not' or 'slightly' difficult to complete and all 84 participants (100%) passed the test of internal consistency.

[Insert Table 1 about here]

The results from the conditional logit regression model based upon the total sample (including proxy respondents), for the self-reporting sample (excluding proxy respondents) and for self-reporting sub-samples partitioned according to cognitive functioning (higher cognitive functioning and lower cognitive functioning) are presented in Table 2. Column (1), comprising the total sample, indicates that participants exhibited statistically significant positive preferences for the lowest risk of future falls (25%) and for improvements in mobility (walking with a frame with one person close by and walking with a stick independently without help) and statistically significant negative preferences for the highest level of pain during rehabilitation (severe pain) and the longest duration of rehabilitation intervention (two hours per day for two months). It can be seen from Column (2) that the results for the selfreporting sample (excluding proxy respondents) are very similar to the total sample. Columns (3) and (4) in Table 2 present the results from the self-reporting sub-samples partitioned according to cognitive functioning. For respondents without cognitive impairment (i.e., MMSE≥24), the conditional logit estimates are broadly consistent with the total sample. However, for individuals with minor cognitive impairment (i.e., MMSE ranged between 19 and 23), the pain attribute became insignificant. These results are supported by application of the Swait and Louviere test which confirmed that splitting the sample based on cognitive functioning, the null hypothesis of equal preferences could not be rejected at the 10% level.

#### [Insert Table 2 about here]

The results from the heteroscedastic conditional logit model to investigate whether selfreporting respondents' characteristics impacted on the error variance are presented in column (5) of Table 2. The MMSE score was included as a dummy variable reflecting higher or lower cognitive functioning. The coefficient relating to cognitive functioning was positive indicating that respondents with higher level of cognitive functioning tended to exhibit higher scale and thus lower error variance, however this was not found to be statistically significant.

Preference heterogeneity was investigated through application of a mixed logit regression model by specifying the coefficients attached to each attribute level ( $\beta_i$ ) to follow a normal distribution with associated mean and standard deviation. Based on the BIC values, the results suggest that firstly, only the attribute levels relating to mobility were found to be statistically significant, and secondly, random coefficients assumed to be independent are preferable. The above findings were then incorporated into the G-MNL model. Column (6) in Table 2 reports results from application of the G-MNL model which accounts for both scale and preference heterogeneity simultaneously. The parameter  $\gamma \mathbb{Y}$  (which governs how the variance of residual preference heterogeneity varies with scale) was estimated both without any boundary restriction and also on two special cases (i.e.,  $\gamma=0$  and  $\gamma=1$ ). For the sake of simplicity, only the preferred G-MNL estimates (selected based on the BIC values) are reported.. In comparison with the heteroscedastic conditional logit model results, the G-MNL model also indicates that the dummy variable attached to cognitive functioning is statistically insignificant (Column (6), Table 2). All other conclusions remain the same across both heteroscedastic conditional logit and G-MNL models principally that: MMSE score is statistically insignificant and only the mobility attribute exhibits robust statistically significant standard deviations.

#### Discussion

This paper investigated the potential role of cognitive functioning in DCE using a sample of older patients following surgery to repair a fractured hip. Preference heterogeneity was found to be significant only for the mobility attribute and no evidence of a relationship between scale heterogeneity and the level of cognitive functioning was found. A limitation of our study was that information relating to MMSE scores for proxy respondents was unavailable and hence they were excluded from the sub-sample analyses. However, proxy respondents made up a small proportion of the total sample. There is evidence from the stated preference literature to indicate that proxy responses may not be equivalent to the responses of people

with cognitive impairment [17,18]. The reliability of proxy responses for DCE's has not been investigated thoroughly to date and is an important area for future research.

There are several possible explanations for our findings. Although it is presently the most widely applied instrument internationally for assessing cognitive impairment, the MMSE may not be the most appropriate test of cognitive functioning for application with DCE studies. In a comprehensive review of screening tests for cognitive impairment Cullen et al. [19] noted that although a total of 39 screening tests were identified which had been designed for this purpose clinician surveys indicate that the MMSE is "overwhelmingly ubiquitous in practice". The MMSE was found to lack coverage in both verbal fluency and reasoning/judgement domains. However, the ability to apply logical reasoning and judgement is clearly an important requirement for a participant to provide meaningful responses to a discrete choice experiment. Therefore although the MMSE appears reasonable at categorising individuals with higher and lower cognitive functioning, it may not provide a good measure of a person's ability to carry out logical reasoning [20]. This may provide at least a partial explanation as to why we failed to observe a consistent relationship between cognitive impairment and scale heterogeneity. Future research is needed to further assess the discriminative abilities of the MMSE in relation to other more comprehensive screening tests in categorising individuals with higher and lower cognitive functioning for the purposes of participation and data analysis for DCE studies.

In practice the impact of the task environment, the complexity of the DCE task and the cognitive capacity of the participant are likely to be highly inter-dependent. Within this study we deliberately sought to simplify the DCE design and minimise the complexity of the DCE task in two main ways. Firstly, by focusing upon four salient attributes with three levels attached to each attribute and secondly, by blocking the design into three versions to reduce the number of choice sets required for presentation [2]. The simplification of the task may therefore have contributed to the main finding of the insignificance of the level of cognitive functioning on scale heterogeneity and it is possible that scale heterogeneity may be more

evident where more complex DCE tasks are conducted. Previous studies conducted exclusively in populations of older people have tested the impact of the complexity of the DCE task, in terms of the mode of administration and the number of choice sets presented [21,22,23]. These studies found that participant understanding and completion rates were significantly elevated using an interviewer mode of administration with visual props (in the form of choice sets handed one at a time to the participant for consideration) as opposed to a traditional self-completion format with all choice sets presented simultaneously in a single questionnaire. Additionally participant fatigue precluded the presentation of more than 6 or 7 binary choice sets within a single interview.

This exploratory study involved face to face interviews which are more expensive than other forms of data collection and hence the sample size was relatively small when compared to samples achieved from other sources (e.g., online panels). However, our sample size is larger than many DCE studies reported in the literature that have also incorporated more advanced modelling approaches [22,24,25,26]. Further research is needed in larger samples and more diverse populations to substantiate these preliminary findings and to investigate the reliability and validity of the DCE approach in populations of older people, including those with mild cognitive impairment.

#### Acknowledgements

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	Self-reported N=74	Proxy <sup>a</sup> N=10
	N (%) <sup>b</sup>	N (%) <sup>b</sup>
Mean age (Std. Dev.) years	80 (8.5)	82 (6.9)
Female	52 (70%)	7 (70%)
MMSE <sup>c</sup>		
Normal (24-30)	48 (68%)	
Mild (18-23)	23 (32%)	
Education <sup>c</sup>		
No qualifications	32 (44%)	5 (50%)
High school	35 (48%)	5 (50%)
Degrees/professional qualification	6 (8%)	0
Live in community	64 (86%)	4 (40%)
Live in residential care	10 (14%)	6 (60%)
Born in Australia <sup>c</sup>	53 (73%)	8 (80%)
Difficulty <sup>c</sup>		
Not	39 (56%)	4 (40%)
Slightly	20 (28%)	4 (40%)
Very or Moderately	11 (16%)	2 (20%)

### Table 1 - Participant Characteristics

<sup>a</sup> Characteristics reflect patients in proxy group with exception of MMSE score which was not available for proxy respondents

<sup>b</sup> Unless otherwise indicated

 $^{\rm c}$  MMSE missing = 3, Education missing = 1, Born in Australia missing = 1, Difficulty missing = 4

Attributes	Description	Attribute levels <sup>†</sup>	Conditional Logit			$HCL^{\ddagger}$	G-MNL <sup>§</sup>		
			(1) Full sample	(2) Self- reported sample	(3) MMSE ≥ 24	(4) MMSE 19~23	(5)	(6)	
Risk	Risk Your risk of falling and breaking another bone at some time point following rehabilitation	eaking another bone	0.088	0.121	0.009	0.282	0.078	0.045	
			[0.110]	[0.103]	[0.136]	[0.185]	[0.096]	[0.254]	
		25%	0.357***	0.373***	0.404***	0.518***	0.369***	1.331***	
			[0.118]	[0.110]	[0.152]	[0.200]	[0.112]	[0.456]	
Pain	n The level of pain you	• •	<b>Moderate</b> pain for 6 to 8 weeks	0.222***	0.214*	0.327**	0.120	0.208**	0.585**
	would need to accept during rehabilitation	o lo o weeks	[0.084]	[0.112]	[0.152]	[0.194]	[0.103]	[0.264]	
	with the aim of recovering your ability to walk short distances	<b>Severe</b> pain for 6 to 8 weeks	-0.369***	-0.332***	-0.378**	-0.209	-0.270***	-0.693***	
			[0.100]	[0.108]	[0.150]	[0.185]	[0.103]	[0.247]	
Effort	<b>T</b> I I I ( (( )	1 ,	-0.013	0.021	-0.114	0.193	-0.019	-0.064	
			[0.098]	[0.100]	[0.133]	[0.180]	[0.091]	[0.205]	
exercising	by working hard and exercising with a	<b>2 hours</b> per day for 2 months	-0.355***	-0.417***	-0.297**	-0.650***	-0.349***	-1.115***	
	physiotherapist	• =	[0.104]	[0.114]	[0.151]	[0.214]	[0.120]	[0.372]	
Mobility Your ability to reco walking following rehabilitation	Your ability to recover	valking following frame with one	0.312***	0.266***	0.341***	0.122	0.241***	0.752**	
			[0.107]	[0.098]	[0.129]	[0.176]	[0.091]	[0.304]	
		Walking with a <b>stick</b> independently	1.066***	1.118***	1.282***	1.094***	1.023***	3.594***	
		without help	[0.149]	[0.116]	[0.158]	[0.220]	[0.169]	[1.014]	

## Table 2 Regression Results

Frame						1.330***
						1.330
						[0.432]
Stick						3.163***
						[0.820]
HET						
MMSE: 24-30 (dummy)					0.206	0.021
					[0.192]	[0.219]
т						0.032
						[0.139]
LL	-219.816	-191.096	-112.877	-60.792	-177.783	-144.593
AIC	455.631	398.191	241.753	137.585	373.565	313.185
BIC	461.756	432.114	272.194	162.186	411.352	363.567
Ν	84	74	48	23	71	71
Obs.	583	513	332	160	492	492

SD.

Notes:  $\dagger$  the omitting levels are: 75% (risk attribute), mild pain for 6 to 8 weeks (pain attribute), 30 minutes per day for 2 months (effort attribute), and wheelchair bound (mobility attribute).  $\ddagger$  HCL: heteroscedastic conditional logit; the null hypothesis for LM test that the error variance is constant across respondents cannot be rejected (LM test statistics = 1.16). § G-MNL: generalized multinomial logit; random coefficients are assumed to be independent,  $\gamma$  is set to be one, 500 Halton draws.

Except for Column (1), all others only used the self-reported sample. Effects coding is used. Standard errors in brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. SD: standard deviation. HET: variables used to model error variance. LL: log likelihood; AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.