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Does Consumer's Working Memory Matter? The Relationship between Working Memory and Selective Attention in Food Choice

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Introduction

The capacity to perform complex cognitive tasks depends on the ability to retain task-relevant information in an accessible state (working memory) and to selectively process information in the environment (selective attention).

Psychology studies suggests a close link between working memory and selective attention. Due to working memory capacity limits, people usually filter out irrelevant information and instead focus on important information.

Will consumer's working memory capacity affect their attention and further their choice?

Survey Design

To address this issue, we designed a choice experiment survey that elicited consumer preferences for fresh strawberries. The strawberries were described by a combination of attributes and levels: Retail Price (\$1.99, \$2.99, \$3.99, and \$4.99), Place of Origin (California or Florida), USDA Organic (Yes or No), Pesticide Residue Free (Yes or No), and Best Use within (2 days or 5 days). All attributes and levels were identified from pilot surveys and literature reviews.

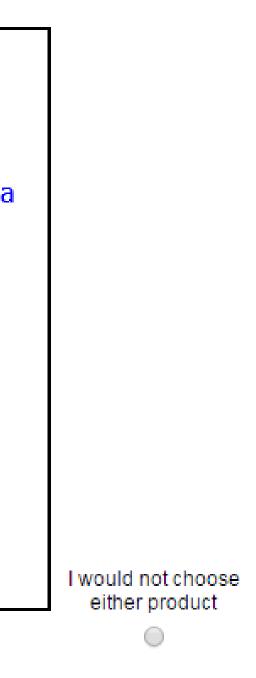
The choice experiment used the optimal orthogonal in the difference design, resulting in 12 pairs, with D-optimality of 90.8%. A 'None' option was added in each choice set in case that respondents are not satisfied with either profile. During the survey, respondents were asked to select attributes they paid attention to and rate the importance of attributes. To measure working memory capacities, respondents were also asked to complete a quiz adapted from the Wechsler adult Intelligence Scale.

The questionnaire was delivered by an online survey company to its representative consumer panels in June 2015, resulting in a final sample of 582 valid responses.

Figure 1. Example of a Choice Task

Which strawberry would yo	u choose?		
Retail Price:	\$2.99	Retail Price:	\$3.99
Place of Origin:	Florida	Place of Origin:	California
USDA Organic:	Yes	USDA Organic:	No
Pesticide Residue Free:	No	Pesticide Residue Free:	Yes
Best Use Within:	5 Days	Best Use Within:	2 Days
0			

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Econometric Methods

First, the Poisson Regression Model is used to examine the effect of working memory capacity on attention.

$$Pr(Y_i = y_i) = \frac{e^{-e^x}}{-}$$

where y_i is the number of attributes that a respondent pay attention to. x_i is a vector of individual-specific characteristics including demographic variables and working memory index.

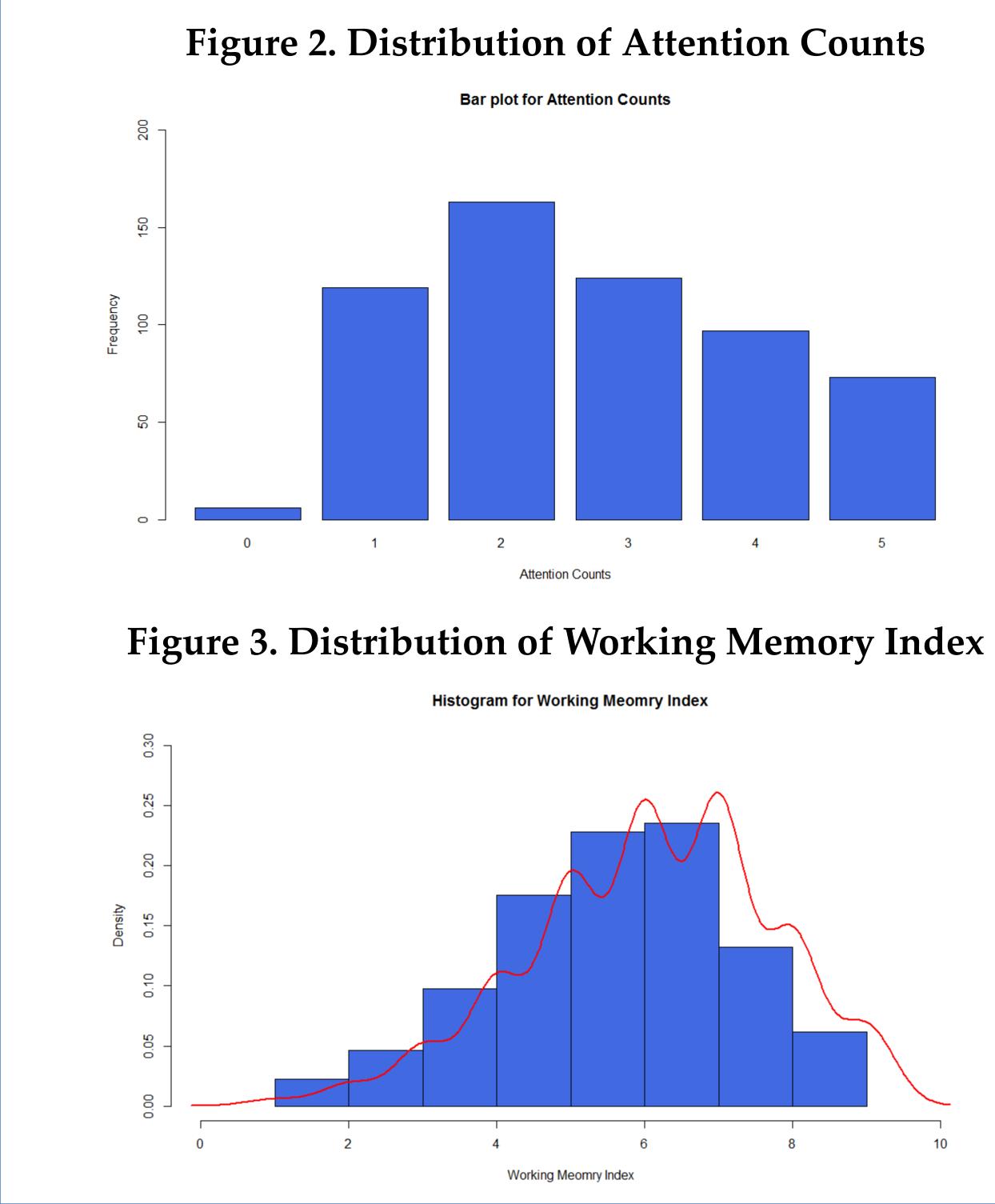
Next, the Latent Class Logit Model is employed to investigate the influence of working memory capacity on choice. The random utility function is written as:

$$U_{jit|c} = \beta'_c x_{jit}$$

where x_{iit} is a vector of strawberry attributes. In the latent formation, parameter heterogeneity across individuals is modeled with a discrete distribution, or a set of classes. The class probabilities are specified by the Multinomial Logit form:

$$\pi_{ic} = Pr(class = c) = \frac{e^{\theta'_{c}Z_{i}}}{\sum_{c} e^{\theta'_{c}Z_{i}}}, \theta_{c} = 0$$

where z_i is modeled to include the working memory index.



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$$(e^{x_i^{\prime}\beta})^{y_i}$$

$$y_i!$$

$+ \varepsilon_{jit}$

 Poisson Regression Model results After stepwise selection, we found that a Poisson Regression Model with only one predictor, working memory index, fitted well. Results show that a one-point increase in working memory index multiplies the expected number of attention counts by 1.03.

Table 1. Poisson Model for Attention Counts

Parameter	Estimate	Standard Error	Wald Confiden		Wald Chi- Square	Pr >ChiSq
Intercept	0.7834	0.0821	0.6224	0.9444	90.97	<.0001
WMSCORE	0.0341	0.0129	0.0089	0.0593	7.02	0.0080
Scale	0.8295					

Latent Class Logit Model results After specifying different numbers of classes, we found that a Latent Class Logit Model with four classes was appropriate. Results show that a one-point increase in working memory index multiplies the odds ratio of falling into Class 2 versus Class 4 by 1.22. The change of parameter estimates suggests working memory directs focus to important attributes.

Retail Price

Place of Origin

USDA Organic

Pesticide Residue Free

Best Use within

None

Latent Class Probability Working Memory Index in Class Probability Model

In conclusion, consumer's working memory capacity will indeed affect their attention and choice. Consumers who have better working memory seems to take more information into account. However, not every information is important to consumers. Some smart consumers tend to focus on important information when making choice.



Estimation Results

Table 2. Latent Class Logit Model

Latent Class Model Estimates					
Class 1	Class 2	Class 3	Class 4		
-0.6214	-2.1985	-0.2287	-0.5487		
(0.0045)	(0.0000)	(0.0000)	(0.0000)		
0.4861	-0.1326	-0.0226	-0.0381		
(0.0465)	(0.2573)	(0.5857)	(0.7446)		
0.0801	-0.1857	0.4765	1.3875		
(0.8022)	(0.1729)	(0.0000)	(0.0000)		
5.0575	-0.0918	0.5352	2.6291		
(0.0000)	(0.4955)	(0.0000)	(0.0000)		
-0.7166	-0.6657	-0.7591	-0.9203		
(0.1264)	(0.0000)	(0.0000)	(0.0000)		
3.0801	-9.6893	-3.9983	3.9684		
(0.0002)	(0.0000)	(0.0000)	(0.0000)		
0.1597	0.1924	0.4862	0.1615		
-0.0875	0.2036	0.0273	0 (6:		
(0.3882)	(0.0471)	(0.7541)	0 (fixed)		

Discussion