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COMPLEXITY AND ACCURACY IN CONSUMER CHOICE: THE DOUBLE BENEFITS OF BEING THE CONSISTENTLY BETTER BRAND

Abstract

This study investigates the impact of choice complexity on consumer utility and choice. The authors find that for choices with up to seven alternatives and seven attributes choice accuracy is affected by three context-based complexity effects but not by task-based complexity. The results suggest that brands that are able to create products that outperform competing products and that do so consistently across multiple attributes benefit from a double bonus. Not only is their product more attractive to consumers, but the accuracy with which consumers choose the product also increases, leading to a further increase in the brand's market share.

INTRODUCTION

The accuracy with which consumers choose their products has important implications for marketing. If consumer choices are not very accurate (i.e., their choices are a poor reflection of their preferences), the impact of improvements in marketing mix variables on product choice probabilities is likely to be low, and brands can find it difficult to position themselves away from other brands. This situation is especially harmful to producers of products that are in some way superior to competing products, because consumers may not take into account the product's strengths. In contrast, if consumer choices are accurate, marketing mix variables may have a much higher impact on consumer choices and product differentiation may be achieved more effectively. Consumers also benefit from greater choice accuracy because the utility of the products they purchase will increase.

In this study we focus on choice set complexity as a potentially important driver of variations in consumer choice accuracy (e.g., Johnson and Payne, 1985). To our knowledge, we are the first to investigate the relationship between choice set complexity and choice accuracy empirically. Another novelty of our analysis is that we combine and compare the effects of task-based complexity with three types of context-based complexity. For this purpose we have integrated complexity and accuracy measures in an empirical mixed logit framework. Some simulation studies exist on the relation between complexity, effort, and choice accuracy (Johnson and Payne 1985) and there is some recent empirical work on the relationship between effort and accuracy (Haaijer et al. 2000) and between preference uncertainty and complexity in judgement ratings data (Fischer et al. 2000). As far as we know, however, no such empirical research exists in the area of choice.

We analyze the impact of complexity on accuracy in consumer utility (which is most relevant for consumer welfare) as well as consumer choice probability (which is most relevant for marketing mix effectiveness) and compare the effects of task-based and context-based complexity (Johnson and Payne 1985). Task-based complexity refers to the number of cognitive steps a consumer needs to choose an optimal product. It is expressed as the combined effect of the number of attributes and the number of alternatives in the choice set. Context-based complexity refers to the difficulty of the trade offs that consumers have to make. We express this effect using three variables based on Shugan (1980): the variability of the attribute utilities of the products in the choice set, the covariance between the attribute utilities of these products, and the difference in total utility between these products.

In modeling terms, we allow for choice set specific variations in choice accuracy. To model consumer choices we use a mixed logit specification (McFadden and Train 2000) allowing for preference variation across individuals, with heteroscedasticity in the errors to capture the differences in error variance across choice sets. We use the estimates as input for two accuracy models in which the dependent variables are accuracy measures for consumer utility and consumer choice probability respectively. The independent variables are the task- and context-based complexity measures. This approach allows us to investigate the relationship between choice accuracy and choice complexity more adequately than previous approaches, because it allows us to formulate the measures of accuracy based on consumers' performance relative to optimal and random behavior. As a consequence, the approach can be applied to compare accuracy across choice sets with different numbers of alternatives, which would not be possible using earlier error variance measures applied by Dellaert et al. (1999) and Haaijer et al. (2000).

Empirically, we investigate the impact of complexity on consumer choice accuracy using consumer choices in experimentally manipulated choice sets of different levels of complexity. We find that utility-based as well as choice probability-based accuracy are driven by variations in all three context-based complexity indexes. In contrast, neither measure of accuracy was significantly affected by variations in task-based complexity in the range of choices in our study (3,4,5 or 7 alternatives with 3 or 7 attributes and varying levels of attribute utility differences).

Managerially, these findings suggest that brands that are able to create greater utility benefits for their products and choose a set of consistently attractive attribute levels benefit from a double bonus. Not only is their product more attractive to consumers, but the accuracy with which consumers choose their products also increases, leading to a further increase in the brand's market share. Behaviorally, our findings suggest that consumers increase their effort in response to shifts in task effects (possibly because they base their choice of effort on the observed number of alternatives and attributes), but do not adjust their effort to changes in context variables sufficiently to maintain the same level of choice accuracy. This result is in line with Johnson and Payne's (1985) suggestion that the effort involved in following a certain choice strategy depends mainly on task variables, while the level of accuracy is driven by context effects.

In the remainder of this paper we first discuss the theoretical and modeling basis for our analysis (section 2). Section 3 covers our experimental study, describing the experimental choice data and our estimation results. In Section 4, we present some conclusions, a discussion, and suggestions for future research.

THEORY AND MODEL

The premise that choice complexity may affect the accuracy of choice outcomes is not new. For example, Johnson and Payne (1985) used simulations to show that the accuracy of different choice rules depends on the complexity of the choice task. Bettman et al. (1990)

examined the cognitive processing requirements associated with various decision rules and concluded that individuals may switch to simpler, less accurate choice rules as choice task complexity increases. Only recently researchers have begun to incorporate variations in accuracy in models of consumer choice. In particular, random utility theory offers a conceptual framework for modeling variations in consumer choice accuracy, because it introduces a random error component in the consumer utility function that can capture unexplained variation in consumer choice behavior (DePalma et al. 1994, Louviere 2001). Some recent studies have acknowledged the role of random error variation in modeling consumer choice and have allowed for differences in unexplained variance in consumer utility functions. These studies use the heteroscedastic logit model (Allenby and Ginter 1995) and parameterized versions of this (Dellaert et al. 1999, Haaijer et al. 2000). However, in this stream of research little attention has been paid to defining a behavioral basis for observed differences in consumer choice accuracy.

In this paper we investigate the effects of complexity on consumer choice accuracy both theoretically and empirically. Figure 1 presents the structure of the analysis and the aspects of the theory discussed in this section. First, we define two choice accuracy measures, one based on consumer utility, which is more relevant for consumer welfare, and one based on choice probability, which is relevant for marketing managers interested in marketing mix effects on product performance (section 2.1). Secondly, we define four different sources of choice set complexity that we analyze (section 2.2). These are based on previous research in psychology and marketing. Thirdly, the expected relationships between consumer choice accuracy and choice set complexity are discussed (section 2.3). Fourthly, we discuss the heteroscedastic mixed logit model that provides the preference estimates and error term variances which are the basis for constructing the choice accuracy and choice set complexity measures from the data (section 2.4).

- INSERT FIGURE 1 ABOUT HERE -

Choice accuracy

Johnson and Payne (1985) define several measures of accuracy of choice heuristics, two of which we adapt for our purposes. Our first measure expresses the accuracy of the consumer choice in terms of achieving the highest possible utility. The second measure expresses choice accuracy in terms of the probability of choosing the optimal product, based upon the discrete distinction between an 'accurate' choice (of the product yielding highest utility) and 'inaccurate' choice (of a sub-optimal product).

For a given consumer with given preferences and choice strategy, the first measure is defined as:

Utility Accuracy (UAc): The expected value (EV) gain of the chosen product over random choice, relative to the EV-gain of the optimal choice over random choice.

Formally this measure is expressed as follows.

(1) $$\text{UAc} = \frac{EV_{\text{strategy}} - EV_{\text{random}}}{EV_{\text{optimal}} - EV_{\text{random}}}$$

Here EV_{random} is the average utility of all the alternatives in the choice set, EV_{optimal} is the maximum utility that can be achieved by choosing the best alternative from the choice set (given the consumer's preferences), and EV_{strategy} is the probability weighted mean utility of the different alternatives given the consumer's choice strategy.

The second measure is defined as:

Choice Probability Accuracy (CPAc): The gain in the percentage of correct choices over random choice, relative to the gain of optimal choice over random choice.

This is formally expressed as:

$$(2) \qquad \text{CPAc} = \frac{CP_{\text{strategy}} - CP_{\text{random}}}{CP_{\text{optimal}} - CP_{\text{random}}}$$

Here CP_{strategy} is the probability that the consumer chooses the best alternative, given his preferences and his choice strategy. If the choice set contains J alternatives, CP_{random} equals $1/J$, the choice probability of each alternative under random choice. CP_{optimal} equals 1, the probability to choose the best alternative if the consumer always makes an optimal decision.

The accuracy measures UAc and CPAc depend on the utility values of the alternatives in the choice set and on the consumer's decision strategy. Both will be captured in the mixed logit model in section 2.4, and the estimates of this model will be used to estimate the UAc and CPAc measures various consumers. The UAc and CPAc can be used to compare choice sets of different composition such as different numbers of alternatives, something which is not possible for the error variance measure theoretically suggested by DePalma et al. (1994) and empirically estimated by Dellaert et al. (1999) and Haaijer et al. (2000).

From a consumer point of view, UAc is the most relevant measure, since it indicates welfare loss, capturing the fact that choosing a sub-optimal product is almost as good as choosing the optimal product. From the producer's point of view, however, CPAc is the more relevant measure, since it is directly related to market shares.

Sources of choice set complexity

Task-based complexity

The idea of describing the complexity of a choice task in terms of a set of basic cognitive processes required to make a choice has been suggested by several authors such as Huber (1980), Johnson and Payne (1985) and Bettman et al. (1993). Their work draws on Newell and Simon (1972) who suggest that choice strategies can be constructed from a small set of so called elementary information processes (EIP's), which represent cognitive steps that individuals have to take to make their decisions. Examples of EIP's are 'Read', 'Compare', 'Add' and 'Eliminate'. Individuals' choice strategies can be described by combining such elementary cognitive processes. Based on this approach, a measure of decision effort can be developed in terms of the number of EIP's required to select a preferred alternative from a given choice set.

EIP's can be used to compare the complexity of choice problems or to compare the effort required by different choice strategies. We will use them for the former purpose only, to construct a measure of the task-based complexity of a choice set. For each choice set we calculate a score (TASK) based on the minimum number of EIP's required to choose the utility maximizing alternative with certainty. Theoretically, different operations may receive different weights, due to differences in the time required to perform them. However, since previous research has suggested that the effort differences between EIP's are relatively small (Bettman et al. 1990), we assign equal weights to all elementary processes.

If two choice sets have the same number of products and the same number of attributes per product, both will have the same task based complexity, even if attribute values differ between the choice sets. Differences in attribute values can be captured in measures of context-based complexity, which depend on the relative utility position of alternatives and their attributes.

Context-based complexity

Based on Shugan (1980) we distinguish three choice set based measures of choice complexity. The basis of these measures is the notion that an alternative's utility to the consumer is the weighted sum of contributions from the utility of all attributes. To make a comparison between two alternatives, Shugan's model assumes that the consumer studies a random sequence of attributes and considers the corresponding attribute utilities of the two alternatives under comparison. This process continues until the consumer can conclude which alternative gives the highest utility. The (context based) complexity of the choice is driven by the number of attributes that need to be selected so that, with some confidence level given a priori, the choice based upon comparing attribute utilities in this subset is the same as the choice based upon full utility maximization.

The number of attributes that needs to be compared depends positively on the variance of the difference between the utilities of the competing levels of a randomly chosen attribute. It depends negatively on the absolute value of the mean difference between the utilities of the randomly chosen attribute. At a more detailed level, the variance of the difference of utilities can be separated into the sum of the variances of the utility of the randomly chosen attribute for each of the two alternatives, minus two times the covariance between the attribute utilities of the two alternatives. According to this analysis, context-based complexity is affected by three factors:

1. Variance of a randomly chosen attribute utility for each alternative (VAR): the higher this variance, the higher choice complexity.
2. Covariance between the attribute utilities of the two alternatives (COV): the higher this covariance, the lower choice complexity, and
3. (The absolute value of the) difference in utility between alternatives (DIF): the larger the difference in utility between alternatives, the lower choice complexity.

The relationship between consumer choice accuracy and choice set complexity

Based on our analysis of the various factors that make up choice set complexity, we now address the question how complexity may affect choice accuracy. The simulation analysis of Johnson and Payne's (1985) shows that with equal effort, consumer choice accuracy is inversely related to choice complexity. The effect of complexity on accuracy then depends on how consumers adapt their choice strategy and their effort level. In particular, if consumers respond to increased complexity by increasing their effort, the accuracy of their decisions may be stable (or even improve) if complexity increases. Results of Haaijer et al. (2000) suggest that in general consumers' effort responses to increases in choice set complexity are not sufficient to maintain equal choice accuracy. Fischer et al. (2000) analyze consumer preference judgements. They find that, if judgement tasks become more complex in terms of variance, responses take more effort and become less accurate. The latter finding suggests that increases in VAR in a choice context may also lead to less accurate choice responses. Dellaert et al. (1999) find that logit model error increases when price based utility trade-offs increase. This effect also suggests that increases in VAR (i.e., higher price variance), and possibly decreases in COV (i.e., lower correlations between price and other attributes), lead to less accurate choices. To the best of our knowledge no empirical results are available on the relationship between complexity shifts in terms of TASK and DIF and the accuracy of consumers' choices.

Therefore, based on the little empirical evidence that is available we expect choice accuracy to decrease with VAR and to increase COV. We have no *ex ante* expectation for the effects of DIF and TASK-based complexity on choice accuracy. However, based on the findings with respect to VAR and COV, one might expect that as a general trend consumers are under-responding to changes in complexity, in particular to context-based complexity variables. This would imply that increases in DIF would lead to greater choice accuracy, while increases in TASK would lead to lower or equal choice accuracy.

A random coefficients heteroscedastic logit model of consumer choice

The model used to analyze the consumers' choice data and to obtain the preference parameters required for the analysis of the relation between accuracy and complexity is based on the well-known multinomial logit model. To accommodate heterogeneity across respondents, we allow for random variation in the attribute coefficients, and use a random coefficients specification. We use the following notation:

- i respondent ($i=1,...,N$), N is the total number of respondents
- s choice situation ($s=1,\dots,S$), S is the total number of choice situations
- k attribute ($k=1,\dots,K$), K is the total number of attributes considered in all choice situations.
- j alternative ($j=0,1,..,J(s)$), $J(s)$ is the number of alternatives in choice situation s

$X_j = (x_{j1},...,x_{jK})'$ vector of attribute values of alternative j, X_j does not include a constant. Attribute values of attributes that are not considered (in a given choice situation), are set to zero (by normalization).

Let the utility of alternative j to respondent i be given by:

(3) $$V_{ij} = X_j'ß_i \qquad j=1,...,J(s)$$

The consumer choices in the data all contain the option of not choosing any of the products offered, referred to as the 'none'-option. Let alternative j=0 be this none-option, and let its utility to respondent i be given by:

(4) $$V_{i0} = ß_{i0}$$

The none-option differs from the other alternatives in the sense that it does not have any attribute values.[1]

The vector of marginal utilities of the attributes $ß_i=(ß_{i1},...,ß_{iK})'$ and the utility of the none-option $ß_{i0}$ may vary across respondents. This will reflect heterogeneity in preferences. McFadden and Train (2000) show that with such heterogeneity, the mixed logit specification is a flexible tool, which can approximate choice probabilities in a large class of random utility models. We assume that the random coefficients $ß_{i0}$ and $ß_i$ are drawn from the following distribution:

(5) $$ß_{ik} = b_k + u_{ik}, \quad k=0,...,K,$$

1 Equivalently, the utility of the none-option could be normalized to 0, and a respondent specific base level utility (not varying over choice sets or alternatives) could be added to the utility values of the other alternatives.

(6) $u_i = (u_{i0},u_{i1},...,u_{iK}) \sim N(0,O)$

The unobserved characteristics of the respondent enter via u_{ik}, which are drawn from a multivariate normal distribution with mean zero. Note that $ß_i$ is respondent specific but not choice situation or alternative specific. Respondent's *i* choices are all assumed to be based on the same $ß_i$. The parameters in the $(K+1)\times(K+1)$ matrix, O, are to be estimated. For computational convenience, it is assumed that O is diagonal, so that only $(K+1)$ standard deviations $?_k$ need to be estimated. The $ß_{i0}$ and $ß_i$ (or the u_{ik}) vary neither with choice situations, nor with alternatives, and are independent across individuals.

In constructing a choice probability model, we follow the usual random utility framework. Choices are based upon the sum of 'true' utilities V_{ij} and error:

(7) $U_{ijs} = V_{ij} + e_{ijs}$ $\quad j=0,\ldots,J(s),\ s=1,\ldots,S.$

Respondent *i* chooses alternative c in choice situation s if and only if $U_{ics} \geq U_{ijs}$ for all alternatives *j* in that choice situation.

There are two unobserved random variables in this model, with quite different interpretations. The u_i reflect unobserved heterogeneity across respondents; they are respondent specific and do not vary across choice sets or alternatives. They thus reflect a part of consumer preferences which is consistent across different choices. On the other hand, the e_{ijs} vary independently across all choice sets and all alternatives. We refer to them as "errors". In the terminology of Fischer et al. (2000), they could also be called preference uncertainty, leading to inconsistent choice behavior. The essential characteristic of the model – which is typical for the mixed logit model, the mixed probit model and other random coefficients models used in the literature – is that the distinction between the two is identified due to this correlation structure, justifying the interpretation. The unobserved heterogeneity terms u_i fit with perfectly accurate choice behavior of the respondents, while the e_{ijs} capture preference uncertainty, choice inconsistencies, evaluation errors, optimization errors, etc. One way to interpret this, is to see the multinomial logit framework as a tool to approximate the choice probabilities obtained by some decision rule other than perfect full information comparison of all utility values V_{ij}. The size of the e_{ijs} (i.e., the variance of the e_{ijs} relative to the variance of the V_{ij}) then determines the extent to which the actual decision strategy deviates from perfectly rational choice based on full information. Simpler decision strategies then lead to a larger role for the errors.

In a standard multinomial logit framework the e_{ijs} are assumed to be Generalized Extreme Value type I (GEV(I)). They have the same variance (i.e., are homoscedastic), which, by normalization, is set equal to $p^2/6$. The interpretation of the error terms given above, however, makes it plausible that different choice sets can have different levels of error variance. For example, different levels of complexity may lead to different levels of consumer choice consistency for different choice sets, since they lead to the use of different choice strategies. This is in line for example with what the results of Fischer et al. (2000) would predict. They find that if evaluation of the alternatives becomes more difficult, ratings require more effort but still become less consistent. To capture this effect, we incorporate a specific form of heteroscedasticity: the variance of the e_{ijs} can be choice set specific (i.e., depends on s).

To achieve this in a flexible way, we code each choice set to be a specific choice situation s and to have a separate scale parameter l_s that is inversely related to the error variance in that choice set. For this purpose we assume that:

1. e_{ijs} is independent of exogenous variables (X) and random coefficients $(ß_i,ß_{i0})$,

2. all e_{ijs} are independent,

3. e_{ijs} / l_s ~ GEV(I)

These assumptions imply that, conditional on the random coefficients $ß_{i0}$ and $ß_i$, the choice probabilities are given by:[2]

$$(8) \qquad P_{is}(c|ß_{i0},ß_i;\ l_s) = \text{P}(i \text{ chooses alternative } c \text{ in situation } s|\ ß_{i0},ß_i)$$

$$= \exp(\ l_s V_{ic})/S_{j=1,\dots,J(s)}\ \exp(\ l_s V_{ij})$$

This reduces to the familiar multinomial logit choice probabilities if $l_s = 1$ for all choice sets $s = 1, \dots , S$:

$$(9) \qquad P_{is}(c|ß_{i0},ß_i;\ l_s=1) = \exp(V_{ic})/\ S_{j=1,\dots,J(s)}\ \exp(V_{ij})$$

The summation in the denominator is over the $J(s)$+1 alternatives in the given choice situation s (including the none-option). For different choice situations, the choices of individual i are independent conditional on $ß_{i0},ß_i$. Thus the conditional probability for individual i with choice situations $s=1, \dots, S,$ given $ß_{i0},ß_i$, to choose $J(i,1), \dots, J(i,S)$ is:

$$(10) \qquad LC_i(ß_{i0},ß_i;\ l_s) = \prod_{s=1}^{S} P_{is}(J(i,s)|ß_{i0},ß_i;\ l_s).$$

Estimation

To identify this model with multiple scale parameters, we set $l_1 = 1$. We use smooth simulated maximum likelihood to estimate the model. Conditional on $ß_{i0}$ and $ß_i$, the likelihood contribution of a given respondent is given by (10). This is a product of multinomial logit probabilities that are easy to compute. The unconditional likelihood contribution is the expected value of the conditional contribution, with the expectation taken over the joint density of $ß_{i0}$ and $ß_i$. This is a $(K+1)$-dimensional integral for which no analytical expression can be given. It can be approximated by a simulated mean using draws of standard normal error terms, which can be transformed into $ß_{i0}$ and $ß_i$ using (5) and (6). We use T independent draws for each observation, with independent draws across observations. T is chosen prior to estimation; the results we present are based upon $T = 50$. The likelihood contribution $L_i = E\{LC_i(ß_{i0},ß_i;\, l_s)\}$ is thus approximated by

$$LS_i = 1/T \sum_{t=1}^{T} LC_i(ß_{i0t},ß_{it};\, l_s),$$

where the $ß_{i0t},ß_{it}$ are the parameter values corresponding to the draws.

The Law of Large Numbers implies that for large T, LS_i will approximate L_i. Instead of maximizing the sum of the log likelihood contributions, the sum of the log of the approximated likelihood contributions is maximized. Since the e_{ijs} are not simulated, the simulated likelihood function is a smooth (differentiable) function of the parameters to be estimated. The resulting simulated maximum likelihood estimator is asymptotically equivalent to the ML estimator provided that $T\rightarrow\infty$ fast enough (see Hajivassiliou and Ruud 1994, for example). This implies that standard ways of obtaining ML estimates, standard errors, etc. can be used.

[2] Throughout, we also condition on the given product characteristics X, without mentioning this explicitly.

Complexity measures

Since preferences are heterogeneous across respondents, V_{ijk} and the three context based complexity measures vary across respondents. In testing the expected relationships between accuracy and complexity we work with both the average respondent and with randomly chosen respondents (using estimates of the parameters in (5)-(6)). For a respondent with preference parameters b_{ik} , attribute utilities of alternative j are given by $V_{ijk} = X_{ijk}\boldsymbol{b}_{ik}$ and the average attribute utility of alternative j is given by

$$m_{ij} = (1/K)\sum_{k=1}^{K} V_{ijk} = (1/K)\, V_{ij}$$

The three context-based measures for the complexity of comparing alternatives j and j' can be written as

(9) $$\text{VAR} = (1/K)\sum_{k=1}^{K}(V_{ijk} - m_{ij})^2 + (1/K)\sum_{k=1}^{K}(V_{ij'k} - m_{ij'})^2$$

(10) $$\text{COV} = (1/K)\sum_{k=1}^{K}(V_{ijk} - m_{ij})(V_{ij'k} - m_{ij'})$$

(11) $$\text{DIF} = |\, V_{ij} - V_{ij'} \,|$$

Accuracy measures

The components in UAc in (1) now can be written as follows:

(12) $$EV_{\text{random}} = (1/J(s))\sum_{j=1}^{J(s)} V_{ij}$$ (average utility)

(13) $EV_{\text{optimal}} = \max_{j=1,\ldots,J(s)} V_{ij}$, (optimal utility),

$$(14)\quad EV_{\text{model}} = \sum_{j=1}^{J(s)} \left[\frac{\exp\left(l_s V_{ij}\right)}{\sum_{j'=1}^{J(s)} \exp\left(l_s V_{ij'}\right)} V_{ij} \right] \quad \text{(probability weighted mean utility).}$$

According to (2), with $\text{CPA}_{\text{random}}=1/J(s)$ and $\text{CPA}_{\text{optimal}} = 1$, CPAc is equal to $(CP_{\text{strategy}} - 1/J(s))/(1-J(s))$, and

$$(15)\quad CP_{\text{strategy}} = \frac{\exp\left(\max_{j=1,\ldots,J(s)} \left(l_s V_{ij}\right)\right)}{\sum_{j=1}^{J(s)} \exp\left(l_s V_{ij}\right)},$$

The accuracy measures UAc and CPAc depend on the utility values V_{ij} of the alternatives in the choice set. The heteroscedastic mixed logit choice model implies that preferences are heterogeneous, implying that different respondents have different UAc and CPAc.

EXPERIMENTAL ANALYSIS OF THE IMPACT OF COMPLEXITY ON ACCURACY

Data

A conjoint choice survey was designed to examine the impact of shifts in complexity on consumer choice accuracy empirically. Consumers were asked to choose between various hypothetical yogurt products. The description of these products was based on attributes of yogurt products available in various stores and self-service restaurants, interviews with expert consumers and attributes used in previous research (Ter Hofstede et al. 1999). The survey varied the level of complexity by introducing several different versions. The preamble to the survey asked respondents to imagine that they were having lunch in a self-service restaurant and deciding which yogurt to buy for dessert. They were instructed that yogurts were identical on all attributes not mentioned in the alternatives and that they were available in all their favorite fruit-flavors. Respondents also had the base option of not choosing any of the yogurt products in the choice set.

The survey was divided into 2 parts of 8 choice sets each. The first part consisted of 8 choice sets of two alternatives and the base of not buying either of the alternatives. The alternatives of the choice sets were constructed based on a randomized main effects only 2^3 fraction of a 2^7 full factorial design with its fold-over (see Louviere and Woodworth 1983). This first part of the survey was identical for all respondents. For the second part of the survey respondents were randomly assigned to one of 6 treatment conditions. Respondents in each of the 6 groups were presented with a further 8 choice sets. Choice sets in the different conditions were constructed so as to vary systematically their TASK, VAR, COV and DIFF scores (see sections 2.1 and 2.2). In particular, differences in complexity were created by altering the number of attributes (condition 1), the number of alternatives (conditions 2 and 3), both the number of alternatives and covariance between alternatives (condition 4), and the relative difference in attribute levels in the choice sets (condition 5). One control condition (condition 6) identical in structure to the choices in the first part of the survey was included also. Table 1 summarizes this structure. Table 2 provides the attributes and their levels in the different conditions. These attributes and their levels were selected based on an exploratory analysis of the different yogurt products available in several self-service restaurants and some interviews with regular yogurt consumers.

Choice sets in condition 1 of the second part were constructed on the basis of a 2^3 full factorial design in 4 profiles with its fold-over. This design was repeated once in a different order to construct 8 choice sets. Choice sets in conditions 2 and 3 were constructed starting from the same 2^3 fraction of a 2^7 full factorial as used in part one. Additional alternatives (3 and 5) were added to the choice sets by randomly assigning alternatives from this same design. Strictly dominated alternatives were swapped with alternatives assigned to other choice sets. Condition 4 differed from the previous two in that one dominated alternative was added to the choice sets used in part 1. These alternatives differed from one of the alternatives in the choice set in terms of only one of the 7 attributes, which was set at the less attractive level. Choice sets in conditions 5 and 6 were constructed identically to those in part 1.

-INSERT TABLES 1 AND 2 ABOUT HERE-

Respondents in the survey were participants in an ongoing consumer panel in the Netherlands. The panel consists of approximately 2000 individuals and is largely representative of the Dutch population in terms of age, sex, income, education and geographical location. It runs on a weekly basis and respondents participate voluntarily. Respondents for this study were screened on being yogurt consumers. Of the 978 members in this subgroup a total of 909 completed the survey successfully.

Results

To calculate the appropriate measures of choice accuracy and complexity, first the heteroscedastic random coefficients model was estimated using data from all conditions in part 1 and 2. The model allowed for heterogeneity in taste between respondents as well as different random error scales (l) for all choice sets. The estimates of the means and the standard deviations of the random coefficients are presented in Table 3. All the means were significant at the 95% confidence level and had the expected signs. The standard deviations of all random coefficients were rather accurately determined, with their confidence intervals bounded away from zero, indicating significant preference heterogeneity across respondents.

- INSERT TABLE 3 ABOUT HERE-

The error scales l_s for all choice sets were also estimated and are presented in Table 4. A likelihood ratio test of the model against the homoscedastic case with $l_s = 1$ for all s showed that heteroscedasticity is highly significant (a Chi-squared test value of 388.72 at 55 degrees of freedom). This is in line with the results of Dellaert et al. (1999) and Haaijer et al. (2000), who also observed significant variations in error scales over choice sets of different complexity.

Table 4 also presents the values of the different complexity measures calculated from the model for each choice set, for the consumer with average preferences. There is considerable variation in the values of these measures, as was intended through the structure of the experiments. The correlation coefficients of all pairs of measures all were smaller than 0.40, except for the correlation between VAR and COV which was 0.66.

- INSERT TABLE 4 ABOUT HERE-

The complexity measures were then used to explain the UAc and CPAc scores calculated for each choice set, again for the consumer with average preferences. The UAc and CPAc scores are thus based on the heteroscedastic logit model estimates in Table 3 and the values of l in Table 4. The results of the two linear regressions are presented in Table 5.

For both the UAc and CPAc measure, all parameters for the context based complexity measures were significant and had signs as expected. Accuracy decreased with VAR (variance of the attribute utilities in the choice set alternatives) and increased with COV (covariance between the attribute utilities in the choice set alternatives) and DIF (difference in utility between the alternatives in the choice set). The TASK complexity measure was not significantly different from zero. Thus, accuracy decreased significantly as VAR-, COV- and DIF-based complexity increased, but was not affected by TASK-based complexity. Therefore, consumer utility accuracy and marketing mix response in terms of choice probability accuracy did not decrease significantly as task-complexity increased.[3]

- INSERT TABLE 5 ABOUT HERE -

The results in Table 5 are based on preferences of the average consumer. The model allows us to compute accuracy measures and complexity measures for a consumer with arbitrary preferences, on the basis of which the regressions in Table 5 can be repeated. To see whether the results in Table 5 are sensitive to choosing the average consumer, we randomly drew 500 vectors of preference parameters from their estimated distribution in Table 3, and redid the regressions for the 500 consumers. The results are summarized in Table 6. The findings are in line with those in Table 5. Little effect of task-based complexity is found on UAc and only a minor effect on CPAc. VAR has the expected negative effect in most cases

[3] To test the sensitivity of the results to the definition of our proposed measures of VAR, COV and DIF, we also ran regressions using some alternative specifications for these measures based on the average and sum of all possible comparisons as well as the minimum required number of comparisons per choice set. The results were identical in sign and similar in terms of significance for all measures.

(94% and 91% respectively), and this is significant in 58% of the 500 regressions explaining UAc and 57.6%of the regressions explaining CPAc. COV has the expected positive effect on UAc for 98% of the 500 consumers, and this is significant in 73.2% of all cases. The effect of COV on CPAc, is also positive in most cases (91%), and significant in 50.2% of the cases. The strongest results are those concerning DIF: the utility difference between the products has the expected positive effect on both UAc and CPAc (92% and 90.2% respectively). The effect is significantly positive for 78% of the regressions explaining utility based accuracy and for 88% of the regressions explaining choice probability based accuracy. Thus we can conclude that at the individual level the findings are very similar to those at the aggregate level.

- INSERT TABLE 6 ABOUT HERE -

In summary, both utility based accuracy (UAc) and choice probability based accuracy (CPAc) are affected significantly by shifts in all three measures of context-based complexity. Across the two measures we observe that context-based complexity affects consumer choice accuracy more strongly than task-based complexity. The latter finding suggests that consumers may adapt the effort they put in their decision strategy in response to shifts in task variables (numbers of alternatives and attributes), but not in response to shifts in context variables. Such behavior may explain why accuracy is affected by context variables but not by task variables. This explanation is also in line with Johnson and Payne's (1985) suggestion based on their simulations that the effort involved in following a certain choice strategy depends on task variables only, while given effort, level of accuracy is driven by context effects.

CONCLUSION AND DISCUSSION

We have investigated the relationship between choice set complexity and choice accuracy, using experimental choice data that varied in terms of choice set complexity. To distinguish choice accuracy variation from consumer preference heterogeneity, we have used a heteroscedastic mixed logit framework. We have assumed that preferences are respondent specific and do not vary over choices for a given respondent, while choice errors are independent over choices. By including choice set specific variances of the choice errors, we allow for accuracy variation in a flexible way. To our knowledge, we are the first to investigate the relationship between choice set complexity and choice accuracy empirically. Our analysis is also the first to combine and compare the effects of various sources of complexity (TASK, VAR, COV and DIF) on several measures of accuracy (UAc and CPAc). For this purpose we have integrated the complexity and accuracy measures in an empirical mixed logit framework. Our analysis supplements previous simulation studies on the relation between complexity, effort, and choice accuracy (e.g. Johnson and Payne 1985) and recent empirical work on the relationship between effort and accuracy (Haaijer et al. 2000) and between preference uncertainty and complexity in judgement ratings data (Fischer et al. 2000).

We find that all three context-based complexity measures significantly relate to choice accuracy with signs that indicate that increased complexity leads to less accurate choice. We find no effect of task-based complexity on choice accuracy. An interpretation of this result is that larger task-based complexity may be compensated by increased consumer choice effort, while larger context-based complexity is not. The current data do not allow for a direct test of this hypothesis. In future work we hope to extend our research in this direction. Indirectly, our findings also provide empirical support for Shugan's (1980) analysis of the possible effects of choice set composition on cognitive costs. We observe that accuracy decreases as context-based complexity increases. This finding is in line with Shugan's suggestion that cognitive cost increases with VAR and decreases with COV and DIF, if one is willing to assume that cognitive effort is costly and that consumers trade off the desired level of choice accuracy against effort.

An implication of our findings for marketing management is that if brands are able to distinguish themselves in terms of utility (DIF is large; the brand has a high product utility) and compose a consistent set of attributes (VAR is small) that outperforms the competition on multiple attributes (COV is large), they can gain additional leverage on their preferential position. The reason is that consumers not only prefer these brands (utility is high) but also choose the brands more accurately. Thus, these brands have the double benefit of being better as well as being selected more accurately. On the other hand the market share effects of price or product changes can be small if brands are positioned closely to one another (DIF is small) and their own or relative attractiveness varies over attributes (VAR is high and COV is low). The reason is that consumers' choice responses in the latter situations are found to be less accurate, i.e. consumers' choices are less well in line with consumers' underlying preferences. These inaccuracies may be of benefit to inferior brands, e.g., brands that do not manage to innovate their products over time. Such brands may find that they can maintain a higher market share than if consumer choices were fully accurate. In fact, such brands may benefit from increasing complexity to consumers. For example, by looking for attributes in which they outperform the market leader these brands may be able to increase VAR and decrease COV, thereby increasing the complexity of the consumer choice.

Finally, we believe that the general notion of separating out the average response of a consumer to marketing mix variables from the consistency with which this consumer responds to these variables deserves further investigation. In this area the possible impact of aiding consumers in making better decisions (i.e. decisions that are more in line with their underlying preferences), for example by means of information technology or peer-to-peer information exchanges, on choice accuracy seems to be a promising opportunity for further research.

Table 1

Description of choice task per experimental condition

	Number of Choice sets	*Number of attributes*	*Number of alternatives**	*Attribute level variation*	*Number of observations*
Base	8	7	2	Base level	909 (all)
Condition 1	8	3	2	Base level	153
Condition 2	8	7	4	Base level	163
Condition 3	8	7	6	Base level	137
Condition 4	8	7	3	Base level	164
Condition 5	8	7	2	High difference	145
Condition 6 (control)	8	7	2	Base level	147

*Excluding the base alternative

Table 2

Attributes and levels used in the experiment

		Description of levels	
Attribute	*Present in conditions*	*Base condition*	*High difference condition*
Price	1-6	NLG 1.90	NLG 2.10
		NLG 1.50	NLG 1.30
Fruit content	1-6	10% fruit	15% fruit
		5% fruit	5% fruit
Biological cultures	2-6	Contains biological cultures	Contains biological cultures
		Contains no biological cultures	Contains no biological cultures
Artificial flavoring	2-6	Contains artificial flavoring	Contains artificial flavoring
		Contains no artificial flavoring (all natural)	Contains no artificial flavoring (all natural)
Creamy taste	2-6	Creamy taste	Creamy taste
		Regular taste	Regular taste
Fat content	1-6	0.5% fat content	0.5% fat content
		3.5% fat content	7.5% fat content
Recyclable packaging	2-6	Yogurt container is recyclable	Yogurt container is recyclable
		Yogurt container not recyclable	Yogurt container not recyclable

Table 3

Choice model estimates*

Parameter	*Estimate*	*t-value*
Intercept	-2.611	-11.982
Price	-0.974	-11.288
Fruit content	0.154	11.794
Biological cultures	0.292	9.028
Artificial flavoring	-0.889	-11.866
Creamy taste	0.365	10.411
Fat content	-0.385	-12.762
Recyclable packaging	0.568	11.015
Standard deviations of random coefficients		
SD intercept	1.670	12.629
SD price	0.444	8.684
SD fruit content	0.074	8.655
SD biological cultures	0.113	3.230
SD artificial flavoring	0.575	11.618
SD creamy taste	0.469	11.041
SD fat content	0.286	12.847
SD recyclable packaging	0.123	4.102

*Results for heteroscedastic random coefficients model, for estimates of error scale differences between choice sets (eq. 8) see values of l in Table 4; log-likelihood = -11831.56, BIC = 11616.97.

Table 4

Complexity measures and scale parameter estimates

Choice set and question	*TASK*	*J*	*K*	*VAR*	*COV*	*DIFF*	*l*
Base 1	41	3	7	2.352	0.816	0.007	1.000[4]
Base 2	41	3	7	2.356	0.814	0.001	1.104
Base 3	41	3	7	2.354	0.815	0.003	1.140
Base 4	41	3	7	2.308	0.838	0.097	1.148
Base 5	41	3	7	2.349	0.817	0.013	1.130
Base 6	41	3	7	2.141	0.921	0.430	0.910
Base 7	41	3	7	2.216	0.884	0.279	0.972
Base 8	41	3	7	2.355	0.814	0.002	1.208
1.1	17	3	3	4.247	1.807	0.378	1.509
1.2	17	3	3	4.004	1.928	0.863	1.603
1.3	17	3	3	4.436	1.713	0.000	1.528
1.4	17	3	3	4.383	1.739	0.106	1.563
1.5	17	3	3	2.167	0.797	0.087	1.383
1.6	17	3	3	2.211	0.776	0.000	1.811
1.7	17	3	3	2.109	0.827	0.205	1.260
1.8	17	3	3	1.917	0.922	0.587	1.569
2.1	83	5	7	2.460	1.193	0.002	1.604
2.2	83	5	7	2.178	0.771	0.017	1.704
2.3	83	5	7	2.676	1.224	0.043	1.374
2.4	83	5	7	1.433	0.587	0.013	1.662
2.5	83	5	7	2.278	1.103	0.004	1.316
2.6	83	5	7	2.115	0.732	0.000	1.881
2.7	83	5	7	2.062	0.945	0.099	1.141
2.8	83	5	7	2.860	1.294	0.000	1.919
3.1	125	7	7	2.959	1.286	0.001	1.596
3.2	125	7	7	1.894	0.833	0.012	1.540
3.3	125	7	7	2.292	0.990	0.089	1.355
3.4	125	7	7	1.610	0.714	0.030	1.523
3.5	125	7	7	2.676	1.224	0.043	1.288
3.6	125	7	7	2.214	0.987	0.000	1.611
3.7	125	7	7	2.278	1.103	0.004	1.521
3.8	125	7	7	1.433	0.587	0.013	1.198
4.1	62	4	7	2.105	0.901	0.245	1.198
4.2	62	4	7	1.547	0.651	0.041	1.692
4.3	62	4	7	2.355	0.814	0.002	1.576
4.4	62	4	7	2.544	1.262	0.003	1.212
4.5	62	4	7	2.356	0.814	0.001	1.622
4.6	62	4	7	2.354	0.815	0.003	2.265
4.7	62	4	7	2.629	1.237	0.026	1.407
4.8	62	4	7	2.352	0.816	0.007	1.698

[4] Not estimated, but normalized to 1.

Table 4, continued

Choice set & Question	*TASK*	*J*	*K*	*VAR*	*COV*	*DIFF*	*l*
5.1	41	3	7	4.271	0.959	0.085	1.204
5.2	41	3	7	4.194	0.997	0.240	0.616
5.3	41	3	7	4.314	0.937	0.000	1.154
5.4	41	3	7	4.179	1.004	0.269	1.114
5.5	41	3	7	4.215	0.987	0.198	0.564
5.6	41	3	7	3.686	1.251	1.256	0.686
5.7	41	3	7	3.945	1.122	0.739	0.298
5.8	41	3	7	4.313	0.937	0.001	1.165
6.1	41	3	7	2.141	0.921	0.430	0.940
6.2	41	3	7	2.308	0.838	0.097	1.026
6.3	41	3	7	2.355	0.814	0.002	1.182
6.4	41	3	7	2.216	0.884	0.279	0.992
6.5	41	3	7	2.356	0.814	0.001	1.342
6.6	41	3	7	2.354	0.815	0.003	0.849
6.7	41	3	7	2.349	0.817	0.013	1.060
6.8	41	3	7	2.352	0.816	0.007	1.226

Table 5

Accuracy model estimates: average consumer*

	Constant	*TASK** *	*VAR*	*COV*	*DIF*	*Adj. R^2*
UAc	0.495	0.002	-0.088	0.327	0.051	0.498
	(7.252)	(0.380)	(-3.684)	(4.984)	(5.794)	
CPAc	0.342	-0.005	-0.102	0.289	0.118	0.658
	(3.655)	(-0.811)	(-3.118)	(3.222)	(9.729)	

* OLS regressions based upon 56 observations; t-values in parentheses.

** TASK divided by 10

Table 6

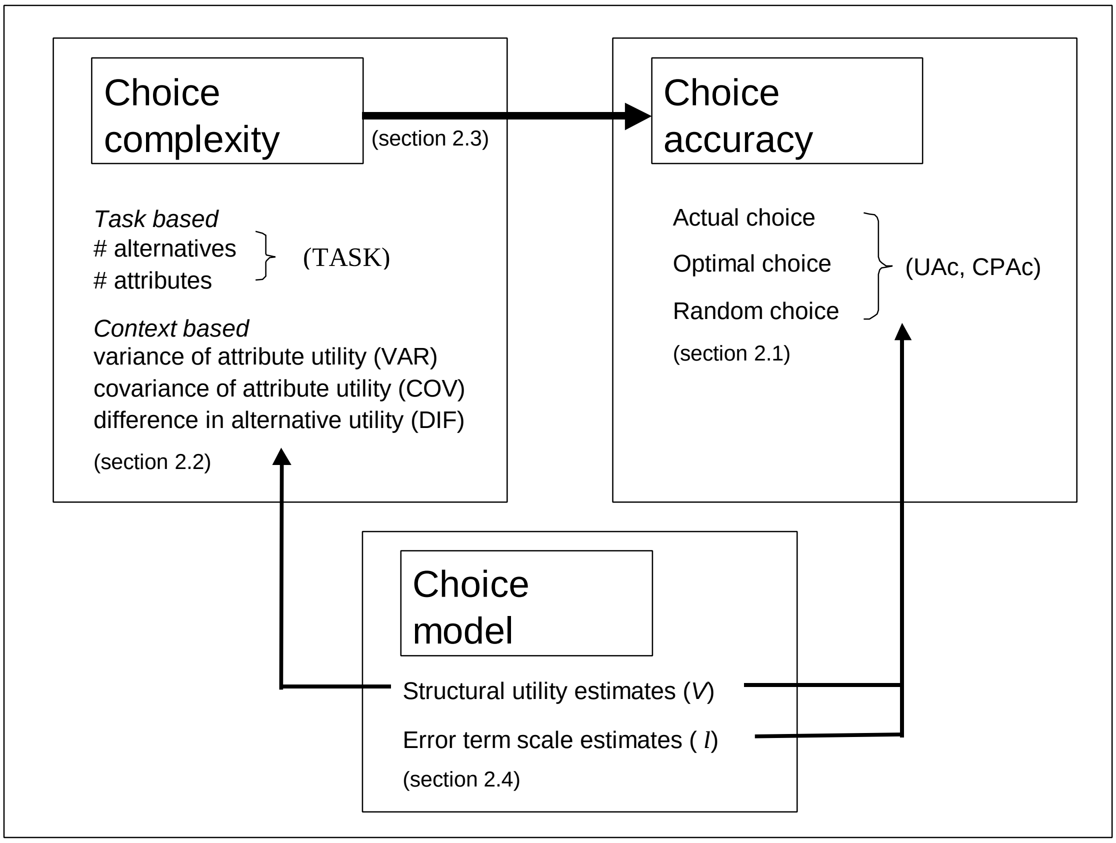
Accuracy model estimates: 500 randomly drawn consumers*

	Constant	*TASK***	*VAR*	*COV*	*DIF*
UAc					
Mean point estimate	0.610	0.003	-0.068	0.202	0.041
Standard deviation of the point estimates	0.249	0.012	0.076	0.151	0.033
Proportion positive point estimates	0.996	0.568	0.060	0.988	0.920
Mean standard error	0.075	0.005	0.027	0.071	0.010
Proportion of coefficients correct and significant	-	0.254	0.580	0.732	0.780
CPAc					
Mean point estimate	0.456	-0.008	-0.073	0.173	0.085
Standard deviation of the point estimates	0.182	0.011	0.073	0.137	0.055
Proportion positive point estimates	1.000	0.268	0.090	0.914	0.902
Mean standard error	0.095	0.006	0.035	0.092	0.013
Proportion of coefficients correct and significant	-	0.412	0.576	0.502	0.888

* 500 OLS regressions based upon 56 observations each.
** TASK divided by 10

Figure 1

Model structure



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