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Response latencies provide information about consumers' choice behavior in a conjoint choice experiment. The authors use filtered response latencies to scale the covariance matrix of a multinomial probit model and show that this leads to better model fit and holdout predictions, even if the response latencies in the holdout task are not used. The authors provide an empirical application along with a tentative explanation for the findings of the effect of response latencies.

Response Latencies in the Analysis of Conjoint Choice Experiments

Choice experiments have become prevalent as a mode of data collection in conjoint analysis. In conjoint choice experiments, respondents make choices from several sets of alternatives. These choices are analyzed with discrete choice models, which produce measurements of preferences for the attributes that comprise the choice alternatives (Louviére and Woodworth 1983). In those discrete choice models, only the observed choices and the design of profiles and choice sets are taken into account. However, with modern computer-assisted data collection, such as the CBC method from Sawtooth Software, information on the time taken by the respondents to make choice decisions is readily available. Although response latencies are collected automatically, without additional cost to the researcher, burden to the respondent, or interference with the choice task, they seem to have been overlooked in the conjoint literature. It is our contention that information contained in response latencies can be useful in obtaining better measurements of (part-) utilities from observed choices.

Response latencies have been studied in psychology, consumer research, and marketing (e.g., Busemeyer and Townsend 1993; Hutchinson, Raman, and Mantrala 1994; Tudor and Carley 1995; Tyebjee 1979). However, most of that research examines various factors that affect the time subjects take to react to stimuli. Here, we propose to use response time to improve the prediction of choice behavior. Response times cannot be used directly, however, because they are affected by the particular choice task used in the conjoint experiment. We therefore describe how raw response times should be corrected for the influence of the task: We filter them to eliminate order effects. We then develop a multinomial probit (MNP) model that incorporates the effect of filtered response time on the estimation of partworths from observed choices. We show that when response times are used to scale the covariance matrix of the MNP choice model, better estimates are obtained for the parameters of interest, which leads to better fit and predictions of holdout choices.

INCLUDING RESPONSE TIMES IN CONJOINT CHOICE MODELS

The Gamma Model for Filtering Response Times

In Figure 1 we show a distribution of response times, and in Figure 2 we show the response time pattern that might be observed in a conjoint choice experiment (the figures are based on the data in our application). The distribution of response times is usually skewed, as is shown in Figure 1. Because this feature is captured well by the gamma distribution, we use that distribution to model response times. The gamma distribution is a flexible two-parameter distribution that is often used for the distribution of timing of events (see Takane and Sergent 1983).

Figure 2 clearly shows an order effect caused by adaptation to the task. We adjust for the order effect before including response times into a choice model by computing a base response time for each choice set, which is the response time expected on the basis of only the sequential position of choice set k for person j:

$$B(t_{jk}) = \exp[\alpha_0 + \alpha_1 \ln(k)], \quad (1)$$

where t_{jk} is the response time by person j for set k. The base response time is estimated through a gamma regression, and expectation is defined as in Equation 1. The ratio of the observed response time for the kth choice set of the jth person to the base, denoted ξ_{jk}, is the filtered response time that is adjusted for the order effect:

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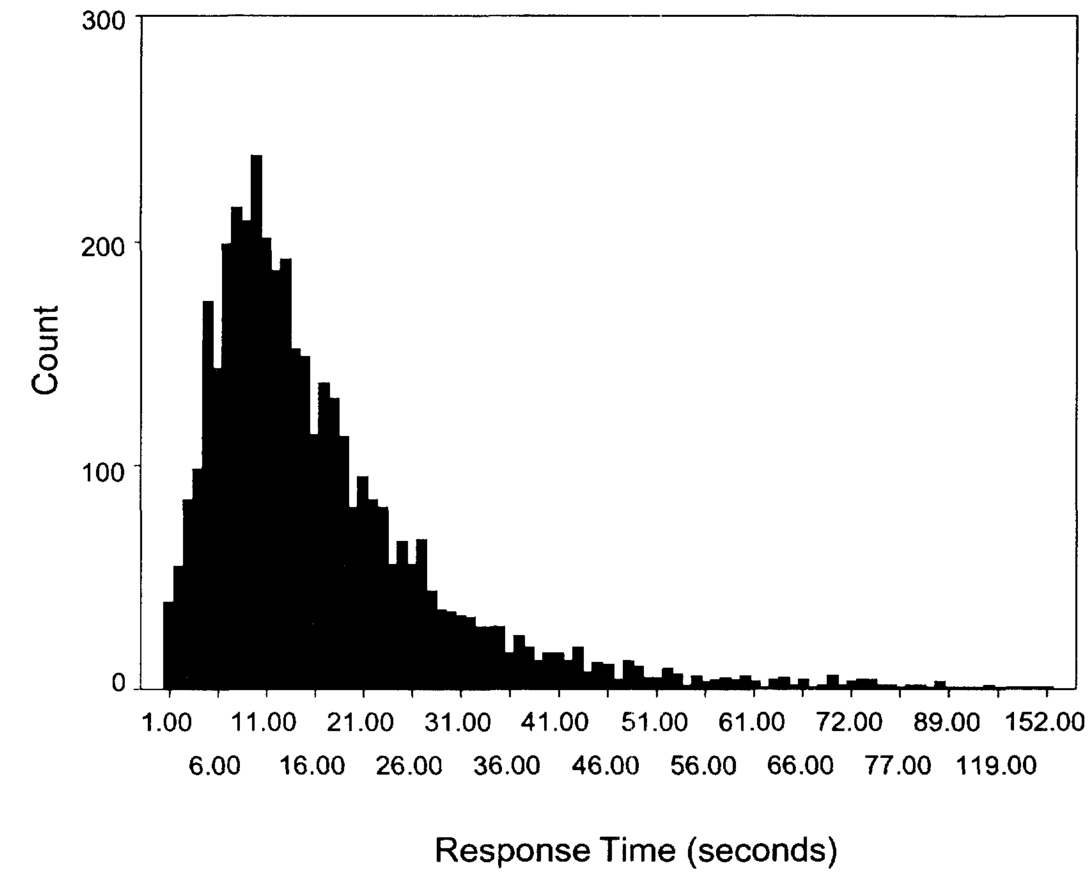
Figure 1
DISTRIBUTION OF RESPONSE TIMES



$$(2) \qquad \xi_{jk} = \frac{t_{jk}}{B(t_{jk})}.$$

The filtered choice time in Equation 2 is less than 1 when the respondent chooses faster than the average time needed for the kth choice set and greater than 1 otherwise.[1]

The MNP Model and Including the Response Times

We start with a random utility choice model for a conjoint choice experiment with J people and K choice sets with M alternatives each, where the Mth alternative is a base alternative. The random utilities of the alternatives for person j are contained in U_j:

$$(3) \qquad U_j = X_j\beta_j + e_j,$$

where X_j is an (H × S) matrix that contains the attributes of the alternatives; H = KM, β_j is an (S × 1) vector of random coefficients, and e_j is the vector that contains the random component of the utilities. We assume normally distributed random utilities—that is, $e_j \sim N_H(0, \Sigma_e)$—which leads to an MNP model. The covariance matrix Σ_e is an (H × H) positive definite matrix. To accommodate heterogeneity across subjects, we allow for random variation in the coefficients by specifying β_j in Equation 3 (Hausman and Wise 1978) as

$$(4) \qquad \beta_j = \beta + \psi_j,$$

with $\psi_j \sim N_S(0, \Sigma_\psi)$ random contributions to the coefficients, independent of e_j. Then

$$(5) \qquad u_j \sim N_H(X_j\beta, \Omega_j),$$

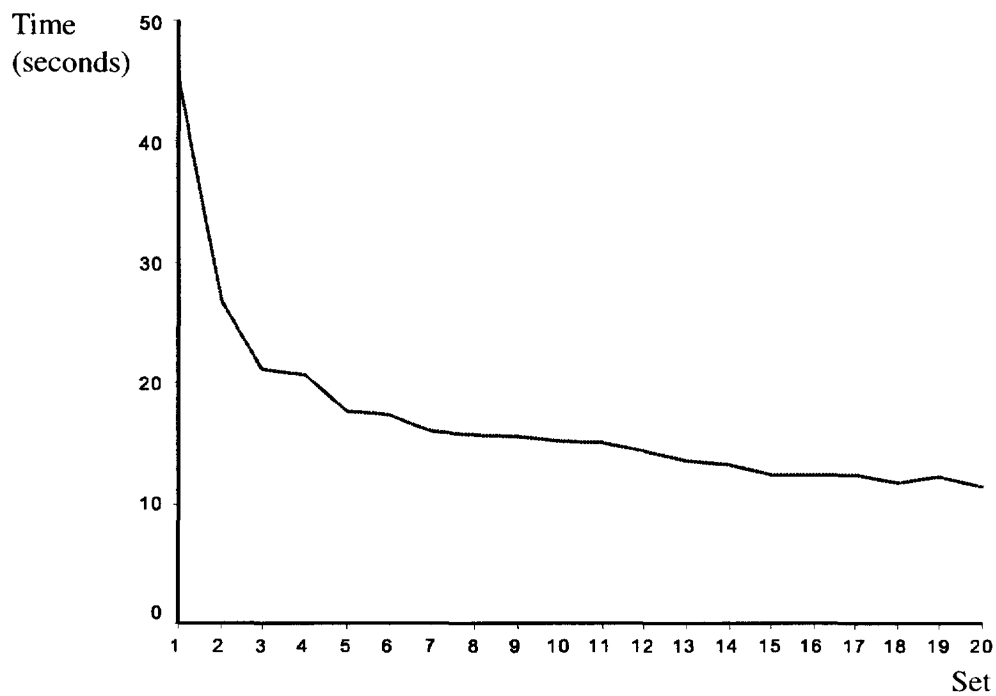
with

$$(6) \qquad \Omega_j = \Sigma_e + X_j\Sigma_\psi X_j'.$$

To arrive at a parsimonious model that is identified, we impose restrictions on Ω. We set $\Sigma_e = I_H$ to be able to make predictions of new profiles. We also parameterize Σ_ψ as a matrix of rank one for reasons of parsimony and identification: $\Sigma_\psi = \sigma\sigma'$, where σ is an S vector of parameters, and S is the number of columns in the X matrix (a similar factor structure was imposed on the covariance matrix of Elrod and Keane's [1995] probit model, in the context of scanner data analysis). We call this the random coefficients (RC) model (Haaijer et al. 1998). For $\Omega_j = I$, the independent pro-

[1]Other specifications have been estimated, and the resulting filtered times from Equation 2 were plugged into the choice model. In particular, models with and without the order effect and with and without respondent heterogeneity terms have been specified in Equation 1, but though they outperformed the choice model without response times, all resulted in a worse fit and predictive validity than the specification in Equation 1.

Figure 2
ORDER EFFECTS IN RESPONSE TIME



bit (IP) model arises. The RC model, unlike the IP, does not suffer from the independence of irrelevant alternatives property (see Haaijer et al. 1998). It enables utilities of the same person to be correlated across choice sets. Therefore, to compute the probability of the observed choices from all choice sets simultaneously, a $K(M - 1)$-dimensional integral must be evaluated in the likelihood function.

On the basis of extant theory (see De Palma, Myers, and Papageorgiou 1994; Espinoza-Varas and Watson 1994; Huber and Zwerina 1996) that seems to agree that response latency relates to choice uncertainty and error, we hypothesize that filtered response times contain information about the variance of the random utility component. Therefore, we specify the RC choice model in such a way that response times scale the (co)variances of the utilities:

$$(7) \qquad \Omega_j = I_H + (X_j \times \xi_j^{\tau/2})\sigma\sigma'(X_j \times \xi_j^{\tau/2})',$$

where $(X_j \times \xi_j^{\tau})$ is an element-by-element multiplication, $\xi_j = (\xi_{j1}, ..., \xi_{jK}) \otimes \iota_M$, and ι_M is an M vector of ones. Here, τ is a parameter that, when negative, causes a slow response to induce a lower variance in the random component of utility, whereas a fast response introduces higher variance. Thus, if the response time parameter is negative, the choice probabilities are more extreme and approximate those of the IP for $\xi_{jK} \to \infty$ if $\tau < 0: p_{jkm}^{SRC} \to p_{jkm}^{IP}$. The choice probabilities approximate a random choice for $\xi_{jK} \to 0$ if $\tau < 0: p_{jkm}^{SRC} \to 1/M$. Conversely, when τ is positive, a slow response leads to higher variances in the random utilities and produces less systematic choices. The effect of response time depends on the sign of the coefficient τ: If it is positive, the effects reverse. We denote the RC model with time scaling in Equation 7 as the SRC model. We estimate the models by maximizing the simulated likelihood. To simulate the choice probabilities in evaluating the likelihood, we use the Geweke–Hajivassiliou–Keane simulator (e.g., Geweke, Keane, and Runkle 1994; Hajivassiliou 1993).

APPLICATION

Study Design

In this section, we describe the results of an application of our model to data from a technological product, collected by Sawtooth Systems. For reasons of confidentiality, we cannot reveal the category or the brand names.[2] The following six attributes were used (the numbers of levels are in parentheses): brand (6), speed (4), technological type (6), digitizing option (3), facsimile (2), and price (4). We use the choices and the response times of a random sample of 200 respondents who each received 20 individualized choice sets with four alternatives, of which the last alternative was "no choice." We use the first 12 choice sets for estimation and the last 8 for prediction, because similar studies involve approximately the same ratio of estimation and holdout choice sets. To accommodate the no-choice option, we include a no-choice dummy in the model. The attributes speed (increasing) and price (decreasing) are coded linearly (levels 1–4); for the other attributes, effects-type coding is used. On the basis of visual inspection of the response time distribution, we selected a sample of 200 responses of which the fastest took more than 4 and the slowest less than 180 seconds. Observations beyond that range appeared to be outliers caused by artifacts in the execution of the task, such as

[2]We are very much indebted to Rich Johnson from Sawtooth Software and to the owner of the data set for letting us use it

guessing or lapses of concentration. We estimate three models—IP, RC, and SRC. To compare the results, we use the likelihood, pseudo R^2, and likelihood ratio (LR) tests and report the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

Results

The average response time is 20.08 seconds across the first 12 choice sets and 17.02 seconds across all 20 choice sets. For the first 12 choice sets, the individual average response times range from 6.17 to 46.17 seconds, which shows heterogeneity in response time across respondents. The average response time of the first choice set is equal to 45.25 seconds, that of the 12th choice set 14.33 seconds, and that of the 20th choice set 11.40 seconds, which shows a strong order effect (see Figure 2). We estimate the gamma model for assessing the baseline response times, which provides estimates of 3.36 (.03), –.43 (.02), and .99 (.03) for the intercept, order effect, and nuisance parameter, respectively (the standard errors are in parentheses). Using these estimates, we filtered the response times and estimated the choice models. In Table 1, we show the results.

In Table 1, we show that the RC model fits significantly better than the IP model, as is evidenced by the LR(16 d.f.) test ($p < .01$). More important, the SRC model including response time produces a better fit than the RC model without response times: The LR (1) test indicates that the contribution of response times is significant ($p < .01$). The SRC model produces the best fit because it accounts for the covariance of utilities, both within and between choice sets, as well as the response time effects.

We also show in Table 1 the estimates of the partworth means β, heterogeneity distribution σ, and response time coefficients τ, as well as the other fit statistics for the IP, RC, and SRC models. The parameter estimates show that a higher speed induces a higher choice probability; two of the

Table 1

ESTIMATION RESULTS

Model	*IP*		*RC*		*SRC*	
Parameter	*Estimates*	$\|t\|$	*Estimates*	$\|t\|$	*Estimates*	$\|t\|$
Brand A β_{01}	.343	7 25*	.404	7.54*	.376	6 88*
Brand B β_{02}	.002	04	–.017	.27	–.022	.33
Brand C β_{03}	.012	23	.071	1.12	.092	1 52
Brand D β_{04}	–.138	2 60*	–.174	2 38*	–.170	2.37*
Brand E β_{05}	.007	15	.018	28	–.010	.15
Speed β_{06}	.090	4 53*	.093	3 57*	.092	3.64*
Technological type A β_{07}	–.443	7 79*	–.561	7.61*	–.544	7.33*
Technological type B β_{08}	.401	8 71*	.493	8.73*	.495	8.88*
Technological type C β_{09}	–.259	4 90*	–.375	4.35*	–.354	4.31*
Technological type D β_{10}	.445	9 66*	.579	9.87*	.545	9.92*
Technological type E β_{11}	–.113	2.20*	–.144	2.18*	–.160	2.37*
Digitizing option (n) β_{12}	–.480	14 55*	– 622	14 04*	–.611	15.66*
Digitizing option (y1) β_{13}	.103	3.48*	.135	3.30*	.143	3.64*
Facsimile β_{14}	–.370	16.88*	– 466	17 26*	–.465	19.19*
Price β_{15}	.271	14.19*	371	15.09*	.353	16.82*
No-choice constant β_{16}	1.704	20.79*	2 025	12.06*	1.861	15.12*
Time Scaling τ	—		—		–1.300	8.48*
Brand A σ_{01}	—		–.045	.70	.028	.60
Brand B σ_{02}	—		.048	.70	.058	1.11
Brand C σ_{03}	—		–.113	1 64	–.134	2.32*
Brand D σ_{04}	—		.051	.67	.014	.22
Brand E σ_{05}	—		–.030	.46	.027	.66
Speed σ_{06}	—		003	.08	.010	.42
Technological type A σ_{07}	—		.148	1.61	.065	.86
Technological type B σ_{08}	—		–.084	1.15	–.070	1.21
Technological type C σ_{09}	—		171	1 65	.118	1.46
Technological type D σ_{10}	—		– 209	2.69*	–.102	1.89
Technological type E σ_{11}	—		030	36	.059	1.02
Digitizing option (n) σ_{12}	—		194	3.82*	.135	3.99*
Digitizing option (y1) σ_{13}	—		– 036	.74	–.043	1.37
Facsimile σ_{14}	—		.127	3 85*	.100	3.64*
Price σ_{15}	—		–.146	4.66*	–.093	3.97*
No-choice constant σ_{16}	—		–1 854	9.20*	–1.484	9.56*
Statistic						
Ln-Likelihood	–2672.259		–2363.042		–2337.303	
AIC	5376.518		4790.085		4740.605	
BIC	5469.049		4895.631		4849.450	
Pseudo R^2	.197		.290		.298	
Holdout Ln-likelihood	–1710.565		–1552.031		–1551.363[a]	
					–1528.261[b]	

*$p < .05$.

[a]Excludes times in the holdout data.

[b]Includes times in the holdout data

technological types are valued positively and three negatively, and the last level has a partial utility of almost zero. The presence of a digitizing option is valued positively, the presence of a facsimile is valued negatively, and a higher price is valued less than a lower price. In all models, only two of the five brand parameters are significant. The no-choice constant is relatively large, which is explained by the fact that the no-choice option was chosen in 43.1% of all cases. The fairly large differences that occur in fit between the IP and RC models accrue from the differences in the estimates of the covariance parameters. Table 1 shows that in the RC model, as well as in the SRC model, almost all the σ parameters related to the attributes digitizing option, facsimile, and price and the no-choice constant are significant, whereas (with one exception) no brand parameter is significantly different from zero.

The estimated value of the response time parameter τ is negative and significantly different from zero ($p < .01$). This means that when respondents take more time, after accounting for the order effect, the variances of the coefficients are reduced, and consequently, choice probabilities become more extreme; that is, choice uncertainty is reduced, and choices become more systematic. This may be observed from Table 1; whereas the estimates of the βs are hardly affected by the inclusion of the filtered response times, the magnitude of the estimates of most of the (significant) σ parameters reduces. In other words, the inclusion of response times in the random coefficients model explains a large part of the variance in utilities. The inclusion of the filtered response times seems to produce somewhat more accurate estimates for the attribute-level parameters. This can be seen from the t-values in Table 1, which tend to be higher in the SRC than the RC model. This shows that including the response times helps in estimating the attribute-level parameters more accurately.

We test the performance of our SRC model by making predictions on eight holdout choice sets on the basis of the parameter estimates shown in Table 1 and comparing the predictions with the IP and RC models. There are two possible ways to predict the choices in the holdout sets with the SRC model. First, the holdout response times can be ignored so that only the β and σ estimates are used for prediction. Second, the predictions can be based on the response times measured for the holdout sets, and therefore all parameter estimates are used in the predictions. The first predictive test is a stronger one, because response time is omitted from the SRC model and predictions for the RC and SRC models are based on the same parameters (different values). When we include the response times in the predictions, we compute the filtered response time for the holdout choice sets. Table 1 shows the log-likelihood for the SRC model both with and without the use of the response time, as well as for the IP and RC models. Table 1 shows that the RC model produces better predictions than the IP model. Furthermore, the SRC model without response times produces better predictions than the RC model. Thus, even when response times were excluded in the holdout predictions, the SRC model shows a better predictive performance than the RC models that did not use response times in estimation. We conclude that these results provide evidence that the estimates of the parameters have improved because of the inclusion of response times in the RC model. In addition, if the holdout response times are included when the SRC model is used for predictions, the results improve even further and become substantially better than for the RC model.[3] These results are supported by the computation of a managerially more insightful statistic: the hit rate in the holdout sample. For the RC model, this hit rate was 51.1%, and for the SRC model 52.0%. Both hit rates are well above chance, but the difference is small (24 hits), because hit rates are based only on the highest utility and thus neglect part of the information contained in the likelihood. Nevertheless, the results support the SRC model.

CONCLUSIONS AND DISCUSSION

Including response times in choice models in the way we propose results in better fit, provides more narrow confidence intervals of the choice model parameter estimates, reduces heterogeneity, and provides better holdout predictions. Considering that response times are collected unobtrusively, at no additional cost to the researcher or burden to the respondent, we see no reason for ignoring this potentially valuable source of information that is automatically collected by the most popular commercial software for conjoint analysis.

In our empirical application, the estimated response time parameter is negative, which implies that if subjects spend more time processing the information presented on the alternatives, choice heterogeneity decreases so that the choice pattern approximates that of the independent probit model. The "ability to choose" (De Palma, Myers, and Papageorgiou 1994) increases, as is evidenced by more extreme choice probabilities. These results are in line with those of Huber and Zwerina (1996), who show that when choice sets are more balanced in utility, people take more time to come to a decision and therefore make less error-prone choices, which leads to better estimates. However, this need not always be the case. We analyzed data from another study, which was also on a technological product.[4] The analysis showed a positive effect of response times in the model ($\tau = .61$, $p < .05$), which indicates that decisions made more quickly were more systematic than those that took more time. The estimation and validation results were consistent with those in the study reported previously. The log-likelihood of the SRC model with response times was higher than that of the RC model without response times for the estimation (–1504.12 versus –1506.38) and the holdout (–677.64 versus –681.00) data. Here, response times were not even available in the holdout data, yet including them in the estimation again produced better results.

As a tentative explanation for the difference in findings between the two studies, we notice that in the study reported in this article, all attributes are utilitarian (objective), and brand names are not very familiar (most of the brand intercepts are insignificant). We conjecture that in this study, the time consumers take to make a decision increases as choice

[3]In addition, we compared our model with a mixture of multinomial logits as another benchmark that includes heterogeneity. The S = 3 class model was optimal, as judged by BIC (S = 2: 5416.17, S = 3. 5130.81, S = 4: 5167.83, S = 5: 5325.70). This model has a higher BIC than either the RC or SRC model. In addition, the log-likelihoods in the estimation (–2370.82) and holdout (–1555.35) data are higher than those for the RC and SRC models, which supports the performance of our models.

[4]This study comprised J = 200, S = 22, calibration data with K = 8 and M = 4, and holdout data with K = 4 and M = 3.

task complexity increases, which leads to a positive relationship between choice complexity and response time. This relationship between response time and task complexity has been confirmed repeatedly in psychological experiments (Bockenholt et al. 1991; Espinoza-Varas and Watson 1994; Hendrick, Mills, and Kiesler 1968). A longer response time indicates more cognitive processing of the attribute information presented in the task. The more time respondents take in making choice decisions, the greater the cognitive capacity devoted to that task and consequently the better prepared they are to make the decision, all other things being equal. In other words, as more information is extracted from the conjoint task and processed, consumers improve their ability to choose, which leads to more systematic choice decisions (De Palma, Myers, and Papageorgiou 1994).

In contrast, the second study (not reported here) involved at least two experiential (subjective) attributes and brand names that may have been well known (all brand intercepts were significant). The literature on attitude accessibility (Fazio 1989; Fazio, Lenn, and Effrein 1984) shows that respondents who have a strong (positive or negative) experience with a brand are likely to respond quickly to an inquiry about the brand and the attitude is more likely to predict future behavior. This arises because subjects retrieve information about their preferences from memory. Accessibility is better for strong preferences, so they are likely to retrieve their attitudes more quickly and make faster and better choices. Memory access is relevant if subjects make decisions primarily on the basis of previously formed attitudes for the brands, which occurs, for example, when category familiarity is high. We hypothesize that this also occurs if the conjoint design includes a large proportion of experiential (subjective) attributes (Havlena and Holbrook 1986; Holbrook and Hirshman 1982). Category experience may help the consumer process the attribute information presented in the task. In these situations, short response times result from fast memory retrieval rather than information processing and thus reflect strong (negative or positive) attitudes toward the brands in the choice set. Consequently, a probabilistic choice model predicts more systematic choice behavior for short response times, everything else being constant, which leads to a positive response time coefficient in our proposed model.

The issue of the effect of response time on choice is connected to the frequency of choosing the no-choice option. Pollay (1970a, b) argues that a choice maker engages in a cost–benefit analysis: Whenever the opportunity cost of the allocated cognitive capacity exceeds the expected benefit from the choice decision, the person terminates the analysis and makes an impulsive decision. Dhar (1997) states that choice processes leading to a no-choice decision take more time than choice processes leading to a real choice. However, Johnson and Orme (1996) report the reverse. The findings in the reported application are in line with Johnson and Orme: The average response time for the no-choice option equals 15.72 seconds compared with 18.00 seconds for the attribute-based profiles ($p < .01$). However, the findings for the second study, in which the coefficient of the no-choice option was positive, are reversed: The average response time was 21.33 seconds for the no-choice alternative and 18.33 seconds for the attribute-based profiles (difference significant at $p < .05$). The latter is close to the value found in the first study. Those findings are in line with Dhar's (1997). We may explain this as follows: If the choice process is based on retrieving brand and experiential attribute information from memory rather than processing objective attributes, the response time of the no-choice option tends to be longer rather than shorter than that for the choices of well-known brands. In the former case, a longer response time indicates a lack of information in memory, whereas in the latter, it may indicate a fast retrieval and processing of attribute and nonattribute information about well-liked brands. A problem complicating these explanations is that both processing of attribute information and accessing memory may operate at the same time within a single study, and differences may be a matter of degree.[5]

We emphasize that our explanation is speculative, and alternative explanations may be available. One such alternative explanation may be a shift from compensatory to noncompensatory choice rules among the attribute-based alternatives, if the time required for the choice decision is anticipated to exceed the time subjects are willing to spend. Although the total time spent on the attribute profiles is similar across the two studies, shorter times lead to less systematic choices in the reported application. This application also involves more choice sets, profiles, and attributes and thus probably a more complex choice context. As response times tend to grow longer, subjects may resort to noncompensatory choice rules (Andrews and Manrai 1998) to limit the time spent in making the choice decisions, which leads to choices being less well predicted by the compensatory probit model and apparently becoming less systematic.[6] Respondent characteristics could help explain the differences in response time and the effects of these differences on choice. Collecting data on those respondent characteristics would enable specific hypotheses to be tested. We suggest these as topics for further research.

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[5]We have investigated this issue further by decomposing the likelihood of the models with and without response times in two components: one for the no-choice option and one for the attribute-based alternatives. In both studies, we observe that including response times improves the likelihood of the attribute-based alternatives, whereas the likelihood of the no-choice alternatives is not affected or deteriorates.

[6]We thank one reviewer for pointing to this explanation of the differences between the two studies.

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