Adjusting Stated Intention Measures to Predict Trial Purchase of New Products: A Comparison of Models and Methods

Author(s): Linda F. Jamieson and Frank M. Bass
Source: *Journal of Marketing Research*, Vol. 26, No. 3 (Aug., 1989), pp. 336-345
Published by: American Marketing Association
Stable URL: http://www.jstor.org/stable/3172905
Accessed: 17-08-2017 12:27 UTC

.... RESEARCH NOTES AND COMMUNICATIONS

LINDA F. JAMIESON and FRANK M. BASS*

Several of the largest marketing research suppliers estimate that 70 to 90% of their clients use purchase intention scales in some form on a regular basis. Though there have been many studies of purchase intention, relatively few researchers have tried to relate purchase intention to actual purchase behavior. Those who have attempted to relate the two often have found substantial variation between stated intention and actual behavior. The authors have collected what they believe is the largest and most comprehensive database on purchase intention and actual purchase behavior for new products yet developed. They use different models in a comparison of predictive accuracy when stated intentions data are adjusted by separate perceptions of products such as willingness to consult others before purchase, affordability, liking, and availability.

Adjusting Stated Intention Measures to Predict Trial Purchase of New Products: A Comparison of Models and Methods

The collection of purchase intentions data in marketing research has become routine. However, knowledge of the relationship between purchase intentions and actual purchase behavior is rudimentary at best. Developing knowledge of this relationship is especially important for new products, the area in which knowledge is least available. We have collected what we believe is the largest and most comprehensive database on purchase intention and actual purchase behavior for new products yet developed.

Much of the routine collection of purchase intentions data in marketing research has been in connection with purchase prediction for *frequently purchased branded products*. Studies of such products by Gormley (1974), Penny, Hunt, and Twyman (1972), Tauber (1975), and Warshaw (1980), among others, generally have shown a positive association between intention and purchase but have been less predictive of actual behavior than desired. Similarly, studies of purchase intention and actual pur-

*Linda F. Jamieson is Assistant Professor of Marketing, College of Business Administration, Northeastern University. Frank M. Bass is Eugene McDermott Professor of Management, University of Texas at Dallas.

The authors express appreciation to Jack Taylor and Gordon Wyner of M/A/R/C for their support, advice, and counsel and to anonymous *JMR* reviewers for their helpful comments and suggestions.

Journal of Marketing Research
Vol. XXVI (August 1989), 336–45

chase for *generic established consumer durable products,* such as automobiles and appliances, by Adams (1974), Juster (1966), and McNeil (1974), have shown a connection, but not an especially strong one, between purchase intention and actual purchase.

We emphasize the types of products studied in the intentions-purchase literature because we believe product type is likely to have a bearing on *adjusted* intentions data and actual purchase. Kalwani and Silk (1982), for example, found differences between consumer durable and nondurable products. Granbois and Summers (1975) found that the predictive accuracy of subjective choice probabilities varied more across product categories than it did among the respondent types they studied. Moreover, one might ordinarily expect differences in uncertainty levels about *new products,* as opposed to established products, to have a bearing on the relationship between purchase intention and actual purchase as well as on the measures one might use to adjust intentions data in the prediction of purchase. The literature is especially sparse in this area. Sewall (1978) used purchase intentions data to study acceptance of new (redesigned) products and Urban and Hauser (1980) applied weights to intentions scales to predict usage of a new telecommunications product, narrow band video telephone. Still, there is little hard evidence on the predictive accuracy of intentions data for new products. A variety of pretest-market models for evaluating new products, such as the one developed by Silk and Urban (1978), have received widespread application with apparently good predictive results (see, e.g., Urban and Katz 1983). However, these models use intentions data measured after initial use or trial as only one element, among many, in predicting purchase. Moreover, the ASSESSOR model of Silk and Urban is designed to predict market share of a new brand rather than trial purchase of an innovation.

We study trial purchases for 10 *new products,* five durable and five nondurable: home computer, cordless telephone, touch lamp, cordless steam iron, shower radio, pump toothpaste, diet drink mix, fruit sticks, stay fresh milk, and low sodium salad dressing. Warshaw (1980) and Hansen (1972) have emphasized the distinction between intention-behavior relationships for brands and for categories. We confine our study to generic product descriptions rather than brand names.

OVERVIEW OF STUDY

Johnson (1979) surveyed custom marketing research suppliers, advertising agencies, and marketing consulting and modeling firms to ascertain their use of intention measures and to collect information about validation experience. Johnson found that the most popular purchase intention scale was the traditional 5-point purchase intention scale:

1. Definitely will not buy.
2. Probably will not buy.
3. Might/might not buy.
4. Probably will buy.
5. Definitely will buy.

We compare predictions of purchase from three alternative models. In each case, stated intentions data obtained from the 5-point scale are modified to predict trial purchase probabilities. Broadly speaking, there are two ways to modify intent scales to predict trial purchase. One is to apply weights to the fractions in the sample to indicate different intention degrees. If the weighting scheme is constant across products, the forecasting system will require only data about intentions. Another way is to use exogenous perceptual measures of new products on such characteristics as willingness to consult others before purchase, affordability, liking, and availability, which can be done within the context of different models relating intention to trial. Within the range of the products included in our study, we examine the degree to which weighting schemes and perceptual measures of products can describe variation in intentions and purchase relationships.

Our study, along with many others in which intentions are compared with actual purchase behavior, has the potential limitation that purchase measures are obtained from persons who are sampled. To the extent that those sampled have been stimulated to a greater degree of awareness by the perception and intention-to-buy questions, their behavior may be different from the behavior of the population at large. Though we do not have firm data on the seriousness of the contamination problem, a necessary condition for the successful prediction of purchase in the whole population is the successful prediction of purchase that has (perhaps) been contaminated by intentions questioning. We believe that sufficient variation in perception, intention, and purchase over the products studied here makes possible meaningful analysis of the relationships among these measures.

ALTERNATIVE MODELS

Weighting Schemes

With the 5-point intention scale, the following set of purchase probabilities or weights might be associated with each of the five response categories.

Category	*Probability*
Definitely will buy	1.00
Probably will buy	.75
Might/might not buy	.50
Probably will not buy	.25
Definitely will not buy	.00

An overall estimate of purchase probability is obtained by:

$$\text{(1)} \qquad \Pr(\text{Trial}) = \sum_{i=1}^{5} w_i(n_i/N)$$

where:

N = total respondents in the sample,
n_i = number of respondents stating a specific intention response category, and
w_i = weight applied to that response category.

However, because respondents typically do not think in terms of probabilities (Tversky and Kahneman 1974) and because random error is definitional to self-report data (Morrison 1979), many researchers and managers develop and use alternate sets of probabilities or weights. Urban and Hauser (1980) reported that managerial judgment should be used in each industry to derive the weights, but they are usually in the following range: 90% of the "definites," 40% of the "probables," and 10% of the "mights."

An advantage of the weighting scheme approach is that actual trial data are not required in order to produce a forecast. The question we examine here is whether or not one weighting scheme will be adequate for all products and situations.

Modified Beta-Binomial Model

Morrison (1979) developed a model expressing the relationship between true intention, I_t, and stated intention, I_x, based on the assumptions that (1) I_x has the binomial distribution with parameter values I_t and n and (2) that I_t is distributed beta over the population of consumers. Morrison further modified the relationship between I_t and I_x by including an instability parameter and bias parameter, ρ and b respectively. This modified beta-binomial model was used also by Kalwani and Silk (1982). The relationship between stated intention and true intention implied by the beta-binomial model is:

$$E(I_t|I_x) = (\alpha/\alpha + \beta + n) + (n/\alpha + \beta + n)I_x \quad (2)$$

where:

$I_x = x/n$ and x is an integer (arbitrary) indication of stated intention $(0,1,\ldots,n)$ indicating the intention ordering when there are $n + 1$ possible response categories,
I_t = true intention, a probability, and
α and β are the parameters of the beta distribution.

$E(I_t|I_x)$ is the expected value of the fraction of the population expressing the stated unadjusted intention, I_x, that will purchase.

The complete model developed by Morrison including the instability parameter, ρ, and the bias parameter, b, is:

$$P_x = A + BI_x \quad (3)$$

where in equation 3:

P_x = purchase probability of a respondent with stated intention I_x,
$A = [\rho\alpha/(\alpha + \beta)] + [(1 - \rho)\alpha/(\alpha + \beta + n)] - b$,
$B = [(1 - \rho)n/(\alpha + \beta + n)]$,
ρ = probability that there is a change in an individual's true intention
$= 1 - [B(\alpha + \beta + n)/n]$, and
b = systematic bias
$= [\rho\alpha/(\alpha + \beta)] + [(1 - \rho)\alpha/(\alpha + \beta + n)] - A$.

Intentions data are used to estimate one component of the model and then bias and instability parameters must be estimated somehow to adjust the intentions data. Morrison and Kalwani and Silk use actual purchase data to estimate the bias and instability parameters. Therefore, Morrison's modified beta-binomial model standing alone, shown in equation 3, is not a forecasting model as it is usable (i.e., its parameters are estimable) only when both survey results on intentions and followup purchase data are available. Because in practice one would want to predict purchase before purchase data are available, we use our perceptual measures in the estimation of the modifying bias and instability parameters in this beta-binomial model.

Linear Modified Intention Model

It is useful to have available a more precise measure of intention probability than is provided by the 5-point intention scale. Many studies show that stated purchase probabilities generate more accurate forecasts than do discrete measures of intent (Granbois and Summers 1975; Juster 1966). Therefore, in addition to completing the 5-point scale, respondents in our study indicated on a 101-point (0 to 100) scale how likely they were to buy each of the 10 products. Whereas I_x measures a verbal intent level, such as "definitely will buy" or "probably will buy," the values provided by respondents on the 101-point scale (P_x) can be used to attach probabilities to the verbal intent levels. Therefore, if I_x is the intent category x, $\Pr(\text{Trial}|\text{Intentions}) = \Sigma_x \Pr(I_x)\Pr(P_x|I_x)$. Essentially, in this case 5-point intentions are being weighted by the respondents themselves. To account further for respondent error and instability, the linear modified intention model can be written as:

$$\Pr(\text{Trial}) = k\Pr(\text{Trial}|\text{Intentions}) \quad (4)$$

where k = adjustment or instability parameter. The perceptual measures of the new products are used to estimate k and thereby modify intentions.

MEASURES OF MODIFYING FACTORS

Respondents to Johnson's survey also acknowledge that many factors, such as distribution, sampling, type of product, time of year, and area of the country, could affect trial. Using the questions in the Appendix, we developed and obtained the following five measures of perception of each of the 10 products that can be used to modify stated intentions.

—*Awareness*. We measure awareness as the percentage of respondents familiar to some degree with the product, eliminating those not familiar at all with the product. Low awareness clearly is associated with high uncertainty about the product. The uncertainty may not be captured fully by the intention measure.

—*Liking*. We measure liking as the percentage of respondents definitely or probably liking the product. Tauber (1975) reported that the greater the commitment made at the concept phase, the greater the likelihood of a person trying the product.

—*Affordability*. We take affordability to be the percentage of respondents saying that the product is easily affordable. Other factors, including intentions, being held constant, one might expect affordability to have a positive effect on trial.

—*Consult*. We measure this variable as the percentage of respondents who would consult someone/something else before purchasing. Intention to consult indicates curiosity but also suggests uncertainty, and thus one might expect this variable to be related to instability of intention.

—*Availability*. We measure availability as the percentage of respondents who after six months have seen the product. The more readily available a product is, the more easily people can carry out purchase intentions. Hence, we expect this variable to have a positive effect on intention-trial relations.

STUDY DESIGN

Telephone survey questionnaires administered by M/A/R/C were used to obtain the data for our study. Several studies have demonstrated that the quality of data collected by telephone is comparable to that of data collected by personal interviews or mail questionnaires (Tyebjee 1979). Data were collected in three waves over six months from the same sample of respondents. Various measures were obtained from each respondent at three time intervals for approximately five products.

Respondents were contacted initially by telephone between March 26 and April 9, 1985. The first interview averaged approximately 20 to 25 minutes. At this time (referred to as wave 1), six-month purchase intentions, measures of perceptual factors, background classification data, and previous purchase history for other relatively new products were obtained from each eligible respondent.

Three months later, between June 25 and July 8, 1985, respondents were recontacted by telephone (wave 2). The length of this interview was about 12 minutes. At this time information was obtained about acquisitions during the intervening period. For persons who had not purchased a particular product, three-month purchase intent and updated perceptual factors were measured. An attempt also was made to measure and account for possible income changes and unbudgeted expenses faced by respondents during the time interval.

The final telephone interview (wave 3), lasting approximately four minutes, took place betwen September 25 and October 3, 1985. Recontacted respondents were questioned about their trial purchase behavior and changes in their financial situation during the previous three months.

Each of the products was presented in the form of a concise statement describing the major features, benefits, and price ranges. No brand names were used. A sequential monadic design with orders of presentation rotated to minimize order effects was used.

RESPONDENT SAMPLE

Respondents were female heads of household, 18 or older, who were primary participants in the buying decisions of their household.

They were allowed to rate a product or give purchase intent for a product only if they and anyone else in the household had not ever previously purchased the product. For the first wave, 800 respondents drawn from a national random probability sample were surveyed successfully. After three months, 412 of the original respondents were recontacted successfully. Of these, 200 were recontacted after six months.

Though four attempts were made at each wave to contact respondents, the attrition rate was fairly high. The attrition rate was 50% for the last two waves because persons answering the telephone refused to answer screener questions (asking for the original respondent) or for other reasons such as "no longer in household" and "not at home." Cross-classification and chi square tests were used to compare the demographic characteristics and the intention ratings of persons who were recontacted with those of persons who were not. The two groups were not significantly different.

Only the data obtained from the 200 respondents contacted on all three waves were used in the study. Because each of the 200 respondents was exposed to only approximately five products in wave 1, in total there were 921 product exposures (respondents times number of products exposed) in wave 3. Table 1 shows the number of respondents questioned for each product (sample sizes).

TRIAL PREDICTION

Prediction Without Adjustment

Table 1 also indicates the actual conditional probability of trial after six months given six-month purchase intentions [Pr(Trial|Intention Level) = Pr(Trial and Intention Level)/Pr(Intention Level)] for each of the 10 products and Figure 1 shows the conditional probabilities given intention for the five durable and five nondurable products. We see clearly in Figure 1 a generally positive association between intention and trial that is somewhat stronger for nondurable than for durable products.

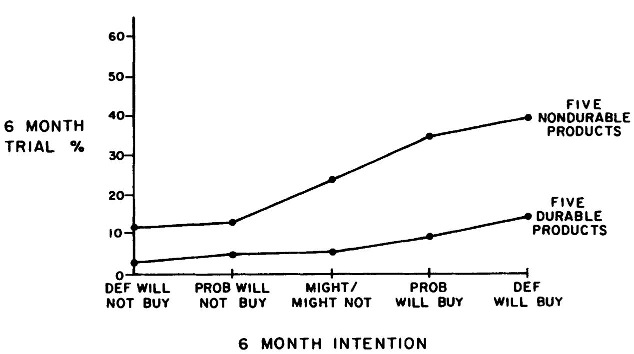
In certain respects, these results may be considered to be at odds with the findings of Morrison and of Kalwani and Silk. Morrison found a flatter relationship between purchase and intentions (adjusted) for appliances than for automobiles. Because these are both durable products, he merely conjectured that the relationship between stated intentions and trial purchase for nondurable products might be weaker. Kalwani and Silk found that a linear relationship between intention and purchase described durable goods and a piecewise linear model worked best

Table 1
NUMBER OF RESPONDENTS QUESTIONED AND CONDITIONAL PROBABILITY OF TRIAL GIVEN INTENTION FOR EACH PRODUCT

		Probability of trial given that stated intention is		
	Number of respondents, wave 3	*Definitely/ probably will not buy*	*Might/ might not buy*	*Definitely/ probably will buy*
Nondurable products				
Pump toothpaste	64	16.7	52.2	52.2
Diet drink mix	60	17.1	25.0	61.5
Fruit sticks	97	15.6	17.2	43.5
Stay fresh milk	99	4.7	0.0	2.8
Salad dressing	100	12.3	25.9	56.3
	420	12.6	24.3	36.0
Durable products				
Home computer	100	3.8	0.0	42.9
Cordless phone	109	11.4	9.1	12.5
Touch lamp	104	2.7	5.6	0.0
Cordless iron	96	0.0	4.0	0.0
Shower radio	92	1.3	9.1	0.0
	501	4.1	5.5	10.0
Grand total	921			

for branded package goods, but they did not specifically compare the relationship between intention and behavior for durable and nondurable products. An inspection of their estimated linear model slope parameters reveals little difference on average between durable and nondurable products. In addition, our durable products, unlike those studied by either Morrison or Kalwani and Silk, are *new* and our nondurable products, unlike those studied by Kalwani and Silk, are generic and not branded. Because consumer planning horizons are frequently shorter for nondurable products than for durable products and because systematic buying plans for new products may differ from those for established products, the relations shown in Figure 1 are not especially surprising.

Figure 1
PROBABILITY OF TRIAL GIVEN INTENTION FOR DURABLE AND NONDURABLE PRODUCTS



Weighting Schemes

Johnson (1979) surveyed experienced users of intentions measures and found that the following weighting schemes were employed by members of his sample.

1. 100% top box
2. 28% top box
3. 80% top/20% second
4. 96% top/36% second
5. 70%/54%/35%/24%/20%
6. 75%/25%/10%/5%/2%

"Top box" refers to the category "definitely will buy" and a weighting scheme of 100% top box means that the purchase probability estimate will equal the percentage of respondents saying "definitely will buy." Using equation 1, we applied the six schemes to the intention data obtained in our study. We report the predicted and observed trial percentages in Table 2.

In comparing predicted trial with actual trial, we see that no one weighting scheme dominates the others for all products. These variations suggest that there is potential in examining perceptual measures to improve predicted trial percentages.

Trial Predictions Based on Product Perceptions

We first estimate the parameters of the *modified beta-binomial* model, shown in equation 3, using intentions data and perception information about the products. The parameters, α and β, are estimated by maximizing the

Table 2
VARIOUS WEIGHTING SCHEMES APPLIED TO STUDY DATA TO ESTIMATE TRIAL

		Trial estimates (%)					
	Actual	Weighting scheme					
Product	trial	1	2	3	4	5	6
Pump toothpaste	42.19	10.94	3.06	13.75	19.50	40.41	18.98
Diet drink mix	28.33	1.67	.47	5.33	8.80	31.50	10.07
Fruit sticks	22.68	4.12	1.15	7.22	11.01	34.24	12.68
Stay fresh milk	3.03	11.11	3.11	13.94	19.76	38.02	18.17
Salad dressing	23.00	5.00	1.40	6.20	8.80	31.53	11.27
Home computer	6.00	2.00	.56	2.60	3.72	26.11	6.68
Cordless phone	11.01	.92	.26	2.02	3.19	26.73	6.56
Touch lamp	2.88	1.92	.54	3.46	5.31	28.33	8.13
Cordless iron	1.04	1.04	.29	2.71	4.38	28.99	8.03
Shower radio	2.17	1.09	.30	1.30	1.83	24.34	5.20
Average absolute error		11.87	13.14	11.01	10.10	17.14	9.87
Average squared error		2.54	3.39	2.07	1.60	4.02	1.44

likelihood function (see Kalwani 1980) on the basis of intentions data for each of the products. In addition, given information on purchase (or trial) for each intention level, we can obtain maximum likelihood estimates of A and B. On the basis of estimates of A and B and α and β, it is possible to solve algebraically for the values of ρ and b. In developing these estimates we follow the methods and measures suggested by Kalwani and Silk. The parameter estimates of equation 3 for each of the 10 products are reported in Table 3. Though many of the parameters have very large standard errors, when the parameter estimates are applied to intentions data for the 10 products (not shown), they yield estimates of trial percentages that closely approximate the observed values.

Next, to replicate a more realistic forecasting setting in which the parameter estimates are not developed directly on the basis of observed trial percentages, we use a jackknife-like method (actually the U-method) in a regression context to estimate ρ and b separately as functions of product perceptions. In this procedure we estimate the relationship for each product using data for the

Table 3
MODIFIED BETA-BINOMIAL PARAMETER ESTIMATES[a]

	Beta-binomial parameters		Linear model parameters		Instability parameter	Bias
	$\hat{\alpha}$	$\hat{\beta}$	$\hat{A}$	$\hat{B}$	$\hat{\rho}$	$\hat{b}$
Pump toothpaste	2.91[b]	2.84[b]	.114[b]	.600	−.463	.088
	(1.491)	(1.442)	(.091)	(.166)		
Diet drink mix	1.08	2.33	.148	.431	.202	.033
	(.448)	(.970)	(.066)	(.179)		
Fruit sticks	3.05	4.55	.129	.248[b]	.281	.173
	(1.50)	(2.237)	(.055)	(.130)		
Stay fresh milk	1.29	1.57	.030[b]	.001[b]	.998	.421
	(.375)	(.455)	(.021)	(.049)		
Low sodium salad	2.17	4.12	.036[b]	.579	−.489	.109
dressing	(.936)	(1.798)	(.033)	(.126)		
Home computer	1.01	3.91	.030[b]	.157[b]	.663	.144
	(.412)	(1.647)	(.021)	(.101)		
Cordless phone	1.27	4.40	.098	.054[b]	.869	.114
	(.530)	(1.870)	(.041)	(.137)		
Touch lamp	2.21[b]	5.92[b]	.000	.101[b]	.694	.243
	(1.103)	(2.997)	—	(.187)		
Cordless iron	4.46[b]	10.57[b]	.000	.033[b]	.843	.286
	(3.654)	(8.687)	—	(.318)		
Shower radio	1.53[b]	7.69[b]	.016[b]	.034[b]	.888	.144
	(.950)	(4.873)	(.050)	(.071)		

[a]The figures in parentheses are the estimated standard errors.
[b]Parameter less than twice its standard error.

Table 4
ESTIMATES OF COEFFICIENTS USED TO PREDICT ρ AND *b* FOR EACH OF THE 10 PRODUCTS AND PREDICTED VALUES OF ρ AND *b*

	$\hat{\rho} = \beta_0 + \beta_1$ *Consult* $+ \beta_2$ *Availability*				$\hat{b} = \beta_0 + \beta_1$ *Liking* $+ \beta_2$ *Availability*			
Product omitted	*Intercept*	*Consult*	*Availability*	$\hat{\rho}$	*Intercept*	*Liking*	*Availability*	$\hat{b}$
None	.672	1.573	−1.448		.246	.471	−.425	
Pump toothpaste	.673	1.462	−1.340	−.269	.243	.473	−.420	.098
Diet drink mix	.655	1.700	−1.560	−.128	.256	.431	−.405	.086
Fruit sticks	.600	1.702	−1.464	.005	.207	.555	−.433	.093
Stay fresh milk	.623	1.575	−1.384	.920	.218	.401	−.348	.335
Salad dressing	.752	1.339	−1.309	.151	.247	.466	−.422	.120
Home computer	.362	2.130	−1.258	1.297	.217	.530	−.411	.192
Cordless phone	.904	1.313	−1.714	.300	.258	.470	−.450	.065
Touch lamp	.669	1.562	−1.444	.636	.247	.455	−.421	.204
Cordless iron	.700	1.588	−1.488	.924	.247	.545	−.466	.356
Shower radio	.663	1.571	−1.435	.866	.345	.319	−.462	.240
Jackknife coefficients	.779	1.382	−1.524		.224	.530	−.436	
Standard error of coefficient	(.384)	(.653)	(.374)		(.109)	(.202)	(.096)	

nine other products to avoid predicting with the same data used to estimate and to examine the stability of the coefficients. For general descriptions of this procedure, see Stone (1974) and Lachenbruch and Mickey (1968). An example of discriminant analysis application in a marketing context is given by Crask and Perreault (1977). It is also described by Cooil, Winer, and Rados (1987).

Using data for each of the 10 products, we studied the five modifying factors previously mentioned using stepwise regression. We find that two factors (perceptual measures), consult and availability, are related significantly to ρ and two factors, liking and availability, are related significantly to *b*. It is worth noting that awareness and availability are highly correlated (r = .886). Table 4 shows the regression equations and parameter estimates for each of the 10 products along with the predictions of ρ and *b* when coefficients used to predict are based on regressions from the other nine products. The estimates appear to be robust with respect to the product eliminated, thus enhancing confidence in use of the measures to predict ρ and *b*.

The statistical results are consistent with the expectations about the influence of the perceptions previously discussed. Consult would be expected to be related positively to instability and availability would be expected to be related negatively. Similarly, liking should favor a positive bias in intentions and availability should diminish bias in intentions.

If intentions are distributed beta, $E(I_x) = (\alpha/\alpha + \beta)$. Therefore, on the basis of equation 3 and this expectation, the expected probability of trial will be

$$P = A' + B'(\hat{\alpha}/\hat{\alpha} + \hat{\beta}). \tag{5}$$

Table 5
MODIFIED BETA-BINOMIAL: OVERALL PREDICTION OF THE PROBABILITY OF TRIAL FROM INTENTION AND PERCEPTION DATA (Model: $P = A' + B'$ $(\hat{\alpha}/\hat{\alpha} + \hat{\beta})$)

	$\hat{\alpha}$	$\hat{\beta}$	$\hat{\rho}$	$\hat{b}$	A'	B'	*E(Ix)*	$\hat{P}$	*Actual trial*	*Difference*
Pump toothpaste	2.91	2.84	−.269	.098	.145	.521	.506	.409	.422	−.013
Diet drink mix	1.08	2.33	−.128	.086	.038	.609	.317	.231	.283	−.052
Fruit sticks	3.05	4.55	.005	.093	.171	.343	.401	.309	.227	.082
Stay fresh milk	1.29	1.57	.920	.335	.095	.047	.451	.116	.030	.086
Salad dressing	2.17	4.12	.151	.120	.111	.330	.345	.225	.230	−.005
Home computer	1.01	3.91	1.297	.192	.041	−.133	.205	.014	.060	−.046
Cordless phone	1.27	4.40	.300	.065	.094	.289	.224	.159	.110	.049
Touch lamp	2.21	5.92	.636	.204	.035	.120	.272	.068	.029	.039
Cordless iron	4.46	10.57	.924	.356	.000	.016	.297	.005	.010	−.005
Shower radio	1.53	7.69	.866	.240	.000	.041	.166	.007	.022	−.015

Average absolute error = .039
Average squared error = .0023

With the estimates of α and β in Table 3 based on intentions data and the estimates of ρ and b in Table 4 derived from product perceptions, it is possible, using definitions of A and B previously provided (we denote A' and B' to indicate that ρ and b have been used as estimated by regression), to predict trial percentages for each of the 10 products. These estimates are reported and compared with actual trial percentages in Table 5. The predictions are very good. This finding suggests to us that the jackknife coefficients in Table 4 could be used along with perceptual data and intentions information to predict trial percentages for other new consumer products.

Next, we estimate trial percentages using the *linear modified intention* model (equation 4) and we compare the results with the predictions from the modified beta-binomial model. Table 6 gives the means of intention probabilities conditional on each of the five intent categories. These means are used as our estimates of $\Pr(P_x|I_x)$. The actual value of k is obtained by dividing actual trial probabilities by Pr(Trial|Intentions). Stepwise regression again is used to find the "best" perceptual predictors of k. Estimates of coefficients and predicted k values for each of the 10 products are reported in Table 7 on the basis of affordability and availability variables. Like the coefficients used to estimate ρ and b, the estimates of coefficients used to predict k appear to be reasonably stable. We note that here, as when ρ and b are estimated in relation to modifying conditions, trial data also are used indirectly to estimate parameters in that the actual k value used in the regressions depends on trial. However, trial data are not used directly in forecasting. The robustness of the parameter estimates in the U-method procedure suggests that the relationships in Table 7 could be used to predict trial for other new consumer products.

We use the estimated value of k to predict trial on the basis of equation 4. The results are reported in Table 8. The predictions are somewhat better than those in Table 5 obtained by the modified beta-binomial model. Therefore, under the conditions we have described in which (1) stated probability of choice is available from respondents along with verbal intention measures and (2) exogenous perception measures are used to predict parameters, the linear modified intention model outperforms the modified beta-binomial. The likely reason seems to be the greater precision of the intent measures we use in the linear modified intent model.

SUMMARY AND CONCLUSIONS

Very few comparative studies have been done of the relationship between intention and behavior for new products at the individual level. Our study helps fill that

Table 6

MEAN 101-POINT SIX-MONTH INTENTION RATINGS FOR EACH OF THE 5-POINT INTENTION SCALE LEVELS

Products	*Definitely will not buy (1)*	*(2)*	*(3)*	*(4)*	*Definitely will buy (5)*
Pump toothpaste	0.00	21.25	47.48	75.56	87.14
Diet drink mix	3.27	15.15	38.33	81.50	0.00
Fruit sticks	.50	9.12	31.24	69.16	85.00
Stay fresh milk	5.91	10.05	43.60	70.60	91.36
Salad dressing	4.19	17.16	48.89	88.55	99.80
Home computer	4.86	15.93	38.00	62.80	100.00
Cordless phone	8.34	11.66	52.50	68.57	100.00
Touch lamp	6.63	15.36	41.39	74.50	55.50
Cordless iron	4.29	21.06	58.88	70.00	100.00
Shower radio	2.69	17.50	58.09	75.00	100.00

Table 7

ESTIMATES OF COEFFICIENTS USED TO PREDICT k FOR EACH OF THE 10 PRODUCTS AND PREDICTED VALUES OF k

(Model: $\hat{k} = \beta_0 + \beta_1$ Afford $+ \beta_2$ Availability)

	Function coefficients			
Product omitted	*Intercept*	*Afford-ability*	*Avail-ability*	$\hat{k}$
None	−.892	1.263	1.180	.857
Pump toothpaste	−.884	1.257	1.170	.857
Diet drink mix	−.845	1.191	1.144	.896
Fruit sticks	−.870	1.202	1.174	.682
Stay fresh milk	−.857	1.279	1.126	.143
Salad dressing	−.948	1.369	1.220	.853
Home computer	−.928	1.371	1.141	.218
Cordless phone	−.892	1.227	1.220	.564
Touch lamp	−.859	1.221	1.173	.202
Cordless iron	−.905	1.272	1.192	.009
Shower radio	−.924	1.273	1.214	.071
Jackknife coefficients	−.899	1.234	1.203	
Standard error of coefficient	(.098)	(.178)	(.097)	

Table 8

LINEAR MODIFIED INTENT MODEL: OVERALL PREDICTION OF PROBABILITY OF TRIAL FROM INTENTION AND PERCEPTION DATA

(Model: Pr(Trial) = kPr(Trial|Intentions))

Product omitted	$\hat{k}$	*P(T|I)*	*P(T)*	*Actual trial*	*Difference*
Pump toothpaste	.857	.481	.412	.422	−.010
Diet drink mix	.896	.284	.254	.283	−.029
Fruit sticks	.682	.288	.196	.227	−.031
Stay fresh milk	.143	.402	.058	.030	.028
Salad dressing	.853	.343	.291	.230	.061
Home computer	.218	.178	.039	.060	−.021
Cordless phone	.564	.228	.129	.110	.019
Touch lamp	.202	.234	.047	.029	.018
Cordless iron	.009	.314	.003	.010	−.007
Shower radio	.071	.166	.012	.022	−.010

Average absolute error = .023
Average squared error = .0008

void. Our results indicate that accurate predictions of purchase probabilities vary considerably across weighting schemes and products. However, it is possible to improve predictive accuracy by measuring and using perceptions that affect and modify the relationship between stated intentions and trial purchase for new products. We illustrate the approach within the context of two different models relating intention to trial: Morrison's modified beta-binomial model and the linear modified intention model.

Though we believe our results are very good for the set of products and conditions we studied and hold promise for the prediction of trial behavior in general, our products and our measures are not exhaustive. However, our results do suggest that extensions could lead to the development of modifiers of intention for use in predicting trial generally. In addition, we think the measures we used in the study, along with the estimated relationships, could be employed successfully to predict trial purchase of other new consumer products.

APPENDIX
QUESTION DESCRIPTIONS

Awareness	How familiar or knowledgeable are you with this product? Would you say you are . . . (READ LIST)?	Very familiar ..... 4 Somewhat familiar ..... 3 Not very familiar ..... 2 Not familiar at all 1
Liking	Now I would like you to think about how much you would like to have this product. Is (ENTER PRODUCT) the type of product you would . . . (READ LIST)?	Definitely like to have ..... 5 Probably like to have ..... 4 Be indifferent to ..... 3 Probably not like to have ..... 2 Definitely not like to have 1
Affordability	In terms of affordability, would you say (ENTER PRODUCT) probably will be . . . (READ LIST)?	Very easy for you to purchase ..... 4 Somewhat easy ..... 3 Somewhat difficult ..... 2 Very difficult for you to purchase 1
Consult	Would you talk to or consult anyone or anything before purchasing this product?	Yes ..... 2 No (SKIP TO Q.18) 1
Availability	Have you ever seen (PRODUCT) in the stores where you shop, or not?	Yes ..... 1 No 2

REFERENCES

Adams, F. Gerard (1974), "Commentary on McNeil, 'Federal Programs to Measure Consumer Purchase Expectations,'" *Journal of Consumer Research,* 1 (December), 11–12.

Cooil, Bruce, Russell S. Winer, and David L. Rados (1987), "Cross-Validation for Prediction," *Journal of Marketing Research,* 24 (August), 271–9.

Crask, Melvin R. and William D. Perreault, Jr. (1977), "Validation of Discriminant Analysis in Marketing Research," *Journal of Marketing Research,* 14 (February), 60–8.

Gormley, Richard (1974), "A Note on Seven Brand Rating Scales and Subsequent Purchase," *Journal of the Market Research Society,* 16 (July), 242–4.

Granbois, Donald H. and John O. Summers (1975), "Primary and Secondary Validity of Consumer Purchase Probabilities," *Journal of Consumer Research,* 1 (March), 31–8.

Hansen, Fleming (1972), *Consumer Choice Behavior.* New York: The Free Press.

Johnson, Jeffrey S. (1979), "A Study of the Accuracy and Validity of Purchase Intention Scales." Phoenix, AZ: Armour-Dial Co., privately circulated working paper.

Juster, F. Thomas (1966), "Consumer Buying Intentions and Purchase Probability: An Experiment in Survey Design," *Journal of the American Statistical Association,* 61 (September), 658–96.

Kalwani, Manohar U. (1980), "Maximum Likelihood Estimation of Zero-Order Models Given Variable Numbers of Purchases Per Household," *Journal of Marketing Research,* 17 (November), 547–51.

——— and Alvin J. Silk (1982), "On the Reliability and Predictive Validity of Purchase Intention Measures," *Marketing Science,* 1 (Summer), 243–86.

Lachenbruch, Peter A. and M. Ray Mickey (1968), "Estimation of Error Rates in Discriminant Analysis," *Technometrics,* 10 (February), 1–11.

McNeil, John M. (1974), "Federal Programs to Measure Consumer Purchase Expectations, 1946–73: A Post-Mortem," *Journal of Consumer Research,* 1 (December), 1–10.

Morrison, Donald G. (1979), "Purchase Intentions and Purchase Behavior," *Journal of Marketing,* 43 (Spring), 65–74.

Penny, J. C., I. M. Hunt, and W. A. Twyman (1972), "Product Testing Methodology in Relation to Marketing Problems," *Journal of the Market Research Society,* 14 (January), 1–29.

Sewall, Murphy A. (1978), "Market Segmentation Based on Consumer Ratings of Proposed Product Designs," *Journal of Marketing Research,* 15 (November), 557–64.

Silk, Alvin J. and Glen L. Urban (1978), "Pre-Test Market Evaluation of New Packaged Goods: A Model and Measurement Methodology," *Journal of Marketing Research,* 15 (May), 171–91.

Stone, M. (1974), "Cross-Validatory Choice and Assessment of Statistical Predictions" (with discussion), *Journal of the Royal Statistical Society,* Series B, 36, 111–47.

Tauber, Edward M. (1975), "Predictive Validity in Consumer Research," *Journal of Advertising Research,* 15 (October), 59–64.

Tversky, Amos and Daniel Kahneman (1974), "Judgment Under Uncertainty: Heuristics and Biases," *Science,* 185 (September 27), 1114–31.

Tyebjee, Tyzoon T. (1979), "Telephone Survey Methods: The State of the Art," *Journal of Marketing,* 43 (Summer), 68–78.

Urban, Glen and John R. Hauser (1980), *Design and Marketing of New Products.* Englewood Cliffs, NJ: Prentice-Hall, Inc.

——— and Gerald M. Katz (1983), "Pre-Test-Market Models: Validation and Managerial Implications," *Journal of Marketing Research,* 20 (August), 221–34.

Warshaw, Paul R. (1980), "Predicting Purchase and Other Behaviors from General and Contextually Specific Intentions," *Journal of Marketing Research,* 17 (February), 26–33.

Reprint No. JMR263106