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Stated intentions and purchase behavior: A unified model ☆

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ABSTRACT

Intentions data often contain systematic biases; intentions change over time and may not accurately predict actual purchases. Ignoring the discrepancies between intentions and purchasing can produce biased estimates of variable coefficients and biased forecasts of future demand. This study proposes a unified model that takes into account various sources of discrepancies between intentions and purchasing and forecasts purchasing probability at the individual-level by linking explanatory variables (*e.g.*, socio-demographics, product attributes, and promotion variables) and intentions to actual purchasing. The proposed model provides an empirically better explanation of the relationship between stated intentions and purchasing and offers more accurate individual-level purchase predictions than do other existing intention models.

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1. Introduction

The widespread use of intentions to forecast actual purchasing relies on the assumption that intentions are good indicators of consumers' purchase behavior (Armstrong, Morwitz, & Kumar, 2000; Chandon, Morwitz, & Reinartz, 2005; Infosino, 1986; Jamieson & Bass, 1989; Sewall, 1978; Silk & Urban, 1978; Urban & Hauser, 1980; Urban & Katz, 1983; Verhoef & Franses, 2003; Whitlark, Geurts, & Swenson, 1993; Wittink & Bergestuen, 2001; Jedidi, Harsharanjeet & DeSarbo, 1997). However, are self-reported intentions really reliable indicators of subsequent purchasing? If they are not—as more and more research implies—how should marketers combine stated intention measures with other available data to predict the probability of purchasing?

Marketing and psychology research has identified three main reasons for differences between stated intentions and actual purchasing: (1) systematic biases in reports of stated intentions (Balasubramanian & Kamakura, 1989; Kahneman & Snell, 1992); (2) changes in explanatory variables, which cause true intentions to shift over time (*e.g.*, unanticipated income shifts and unexpected promotions alter the distribution of true intentions; Infosino, 1986); and (3) the imperfect correlation between intentions and action (Bagozzi & Dholakia, 1999; Gollwitzer, 1999). Individual-level purchasing behavior differs from stated intentions; in addition, individual-level discrepancies do not cancel out in the aggregate and thus create a gap between overall mean stated purchase intentions and the subsequent proportion of buyers. However, most existing studies acknowledge only a subset of these discrepancies and provide inaccurate forecasts and biased estimates of the correlation between intentions and purchasing (Hsiao & Sun, 1999; Young, DeSarbo, & Morwitz, 1998).

Existing aggregate models may be useful for forecasting aggregate sales but can only help managers target individual consumers to a limited extent. Ideally, managers identify the profile of consumers who are most likely to purchase and target them using customized marketing programs. These programs can improve both the effectiveness and the efficiency of marketing efforts. Furthermore, aggregate and disaggregate intention models tend to consider only a binary purchase–no purchase situation. Yet when companies offer multiple alternatives of products and services, managers are interested in predicting purchases of these alternatives. For example, an intention survey for the cellular phone market might ask, “Which usage plan do you intend to sign up for?” with the response options, “high usage plan,” “medium usage plan,” “low usage plan,” and “no plan.” Conventional intention models, which consider only purchase–no purchase decisions, cannot account for these data.

We propose an individual-level intention model that connects stated intentions and purchasing with five new features. The model (1) corrects for systematic intention biases, (2) adjusts for the changes in true intentions over time that are associated with changes in related explanatory variables, (3) allows for an imperfect correlation between intentions and purchasing, (4) includes multiple purchasing levels, and (5) permits individual-level variables and intentions to explain purchasing. Our goal was to develop a statistical

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model that incorporates the intention biases and other factors that cause discrepancies between intentions and purchase; in turn, this model can more accurately predict purchasing. However, our model is not designed to, and probably does not, accurately describe the actual behavioral processes by which respondents determine and report their intentions. Nevertheless, in terms of model fit, our unified model provides a better explanation of the relationship between stated intentions and purchasing than do existing statistical models. Our model can also predict purchasing probabilities at the individual-level more accurately than existing intention models can. Therefore, our research is consistent with a new paradigm in marketing literature that seeks to combine and estimate statements of preference and behaviors (Louviere, Hensher, & Swait, 2000).

In Table 1, we summarize previous research on intention–behavior relationships. For example, Morrison's (1979) influential, modified version of the beta-binomial model made separate estimates of the proportion of consumers who will buy for each response level on a purchase intentions scale. This model acknowledges changes in true intentions over time (i.e., by assuming each new intention is randomly drawn from the intention distribution) and allows for the impact of exogenous events on true intentions (i.e., with constant adjustment). Kalwani and Silk (1982) analyzed the relationship between intentions and purchasing for durable and nondurable goods; they found that the relationship is linear for durable goods but piecewise linear for nondurable goods. Bemmaor (1995) extended Morrison's (1979) model to allow for heterogeneous switching probabilities. Infosino (1986) also interpreted intentions as a monotonic transformation of latent value (willingness to pay) and thus examined the effect of promotions on the probability of purchasing. These examples are all aggregate-level models and thus forecast the same purchase probabilities for all respondents with the same stated level of intention; in this sense, they are only useful for forecasting aggregate sales and cannot identify who is more likely to buy.

More recent models have examined the relationship between intentions and behavior at the segment or individual-level. Morwitz and Schmittlein (1992), for example, divided respondents according to demographic information and developed separate forecasts for each group. Young et al. (1998) and Hsiao and Sun (1999) demonstrated how to recover true intentions from stated intentions in the presence of systematic intention biases. However, neither study took into account the possibility that intentions change over time or the imperfect correlation between intentions and purchasing. With their focus on modeling systematic response biases, these studies simply assumed that true intentions are equivalent to purchasing.

2. Statistical model

The unified and individual-level statistical model that we propose links explanatory variables, stated intentions, and actual purchasing. Suppose there are $n = 1, 2, \ldots, N$ respondents to an intention survey. We assume each respondent confronts a set of ordered intention levels: $j = 0, \ldots, M$.

2.1. Intentions model

Let y_{jn} be a dummy variable denoting observed stated intentions, such that

$$y_{jn} = \begin{cases} 1, & \text{if the } jth \text{ level intention is chosen by the } nth \text{ respondent,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

We begin with the assumption that respondents' reported intentions are a function of their current social and economic status. Accordingly, we let respondents' (true) intention to purchase a product be affected by X_n in an ordered probit model. X_n represents a vector of explanatory variables that could include, for example, socio-demographics, product attributes, and marketing variables.

$$P\left(y_{jn} = 1\right) = \Phi\left(l_{(j+1)n} - \mu_n\right) - \Phi\left(l_{jn} - \mu_n\right), \tag{2}$$

where $j = 0, \ldots, M$; l_{jn} is the threshold for intentions of level j, such that $l_{0n} = -\infty$ and $l_{(M+1)n} = +\infty$; $\mu_n = \alpha_n X_n$ are the deterministic part of

Table 1
Model comparisons.

	Level of modeling	Sources of discrepancy			Modeling approach	Allow for explanatory variables	Data application	Results
		Systematic intention bias	Changes in true intentions over time	Imperfect correlation between true intentions and purchasing				
Morrison (1979)	Aggregate at intention level	Y	Y	Y	Beta-binomial	N (aggregate)	Auto	Linear relation between stated and true intentions
Kalwani and Silk (1982)	Aggregate at intention level	Y	Y	Y	Beta-binomial	N (aggregate)	Durable and packaged goods	Linear model for durable goods and piecewise linear model for packaged goods
Bemmaor (1995)	Aggregate at intention level	Y	Y	Y	Beta-binomial	N (aggregate)	Durable goods, services, and other activities	Heterogeneous switching probabilities; upper and lower bounds
Infosino (1986)	Aggregate at intention level	Y	N	Y	Probit	N (aggregate)	Service	Systematic promotion effects
Morwitz and Schmittlein (1992)	Aggregate at intention level	N	N	N	Segment	Y (individual)	Durable goods	Forecast sales based on segmentation
Young et al. (1998)	Individual	Y	N	N	Bayesian	Y (individual)	Durable goods	Improved estimates and better purchase predictions
Hsiao and Sun (1999)	Individual	Y	N	N	Logit	Y (individual)	Telecomm	Improved estimates and better purchase predictions
This paper	Individual	Y	Y	Y	Multivariate probit	Y (individual)	Automobiles Personal computers	More accurate estimates and forecasts of individual purchase probabilities

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the utility that represents respondents' intention preference and Φ is the standard normal cumulative distribution function. This model assumes that respondents' intentions reflect their social and economic status and that there is no intention bias. For notational convenience, we let $F^*_{jn} = \Phi(l_{(j+1)n} - \alpha_n X_n) - \Phi(l_{jn} - \alpha_n X_n)$ denote the probability that the true purchase intention level of respondent n equals j, with $\sum_{j=0}^{M} F^*_{jn} = 1$.

However, stated intentions do not perfectly reveal respondents' true intentions. Respondents often overreport "desirable" behaviors and underreport "undesirable" ones according to their social desirability bias (Bagozzi, 1994; Bagozzi, Yi, & Nassen, 1999). Similarly, in response to questions about their future demand for a new product or service (especially high-tech products), respondents often exaggerate their demand and produce a positive intention bias (*e.g.*, Klein, Babey & Sherman, 1997). The answer order bias, which refers to respondents' tendency to rate alternatives that appear first on a list higher than those that appear later, can also affect survey results (see Anderson, 1988).

We consider respondents who always overreport their true intentions because this bias is likely in new product intention surveys.[2] We assume a probability π_{jn} that the nth respondent chooses intention level j, regardless of her underlying preference for j $(=0, \ldots, M$, and $\sum_{j=0}^{M} \pi_{jn} = 1)$. Behavioral research has shown that in certain situations respondents give answers that are independent of their underlying preferences. For example, Krosnick (1991) demonstrated that when answering a survey question requires substantial cognitive effort, some respondents simply provide a satisfactory answer instead. They employ various response strategies that include choosing the first alternative that seems reasonable, agreeing with an assertion in a question, endorsing the status quo, failing to differentiate between diverse objects in ratings, indicating a lack of knowledge instead of reporting an opinion, or randomly choosing between alternatives. Zaller and Feldman (1992) confirmed that people simply respond with the answer that is prominent in their minds. Krosnick et al. (2002) further demonstrated that some people never put effort into responding; in the presence of no-opinion options, they refrain from doing the cognitive work required to report their true opinions. However, Sanchez and Morchio (1992) found that even without a "don't know" option, respondents who lack definite answers provide random responses.

In the case of overreporting, the respondent reports an intention level greater than her true intention. To capture this tendency statistically, we assume that the probability of observing the jth reported intention level is

$$P\left(y_{jn} = 1\right) = \pi_{jn}\left[\sum_{i=0}^{j} F^*_{in}\right] + \left[1 - \sum_{i=j}^{M} \pi_{in}\right] F^*_{jn}, \tag{3}$$

for $j = 0, 1, \ldots, M$. This probability contains two components: the joint probability of having an independent intention level j and a true intention level lower than or equal to j, and the joint probability of having a true intention level j and an independent intention level lower than or equal to j. Statistically, Eq. (3) establishes the reported intention as the higher of the independent or true intention levels. We refer to this probability as the *intention bias model*. Although Eq. (3) captures respondents' tendencies to exaggerate their intentions, as noted previously, we do not claim that it represents the exact behavioral process that leads respondents to provide such biased intentions.

In addition, the probability that the nth respondent chooses an intention level π_{jn} should vary across respondents. Let the dummy variable $d_{jn} = 1$ denote the case when respondent n chooses intention level j, irrespective of her underlying preference ($=0$ otherwise). We postulate that the differences in π_{jn} across respondents reflect the influence of demographic variables W_n according to the following ordered probit model:

$$\pi_{jn} = P\left(d_{jn} = 1\right) = \Phi\left(k_{(j+1)n} - \gamma_n W_n\right) - \Phi\left(k_{jn} - \gamma_n W_n\right), \tag{4}$$

where $j = 0, \ldots, M$; k_{jn} is the threshold for intention level j, such that $k_{0n} = -\infty$ and $k_{(M+1)n} = +\infty$. The vector W_n includes variables that may affect the probability of providing biased responses, such as knowledge of the product, education, and gender[3]; γ_n is a vector of the coefficients that measure the effect of these variables.

2.2. Purchasing model

We next incorporate purchasing information. We let the dummy variable $Z_{j^P n}$ denote the purchase decision, such that

$$Z_{j^P n} = \begin{cases} 1, & \text{if the nth respondent purchases at the } j^P\text{th level,} \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Then let μ^P_n be the deterministic part of the utility that describes the purchasing preference of the *nth* respondent. As Louviere et al. (1999) noted, the fundamental latent constructs of preference and utility are stable; after controlling for context effects, we can use intentions to predict actual choices. Hsiao, Sun, and Morwitz (2002) and Taylor and Todd (1995) further showed that purchasing is a function of intentions. On the basis of these empirical findings, we assume that purchase utility depends on latent true intentions at the time of the survey (μ_n) and on changes in the explanatory variables X_n between the time of survey and the time of purchase (ΔX_n). The deterministic part of purchase utility is therefore:

$$\mu^P_n = \beta_n \mu_n + \lambda_n \Delta X_n = \beta_n \alpha_n X_n + \lambda_n \Delta X_n = \alpha^P_n X_n + \lambda_n \Delta X_n. \tag{6}$$

Morwitz, Johnson, and Schmittlein (1993) and Borle, Dholakia, Singh, and Westbrook (2007) demonstrated that consumers who participate in intentions surveys exhibit an increased propensity for purchasing compared to similar consumers who never participated in an intentions survey. Morwitz et al. (1993) also found that this mere measurement effect decreases with respondents' prior experience with the product. To capture the mere measurement effect, Borle et al. (2007) included a dummy variable in their purchase equation that indicates whether a respondent has participated in a survey. However, few study scenarios include an unsurveyed control group. In Eq. (6), we therefore include intention utility and allow its coefficient β_n to differ from 1. If measuring intentions does not change subsequent purchase behavior, the coefficient should remain close to 1; all the coefficients of X_n in the intention utility would then remain the same in terms of purchase utility. However, when β_n varies from 1, it implies that measuring intentions has affected purchasing behavior.

We let $\alpha^P_n = \beta_n \alpha_n$. We also include the vector ΔX_n to capture changes in the explanatory variables that may cause a shift in the purchase utility. For example, marketing managers might plan a 30% price cut for personal computers in the months after they conduct an intention survey. The price drop cannot affect the true intentions that were measured at the time of the survey but probably greatly increases demand at the time of purchase. We thus allow $Z_{j^P n}$ to depend on both X_n (measured at the time of the survey) and the

[2] The underreporting model is similar to that for overreporting. See Hsiao and Sun (1999) for other forms of intentions biases.

[3] Both W_n and X_n must contain at least one nonoverlapping variable for the model to be identified (Hsiao & Sun, 1999).

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changes in these explanatory variables ΔX_n (after the survey). In the ordered probit model,

$$P\left(z_{j^P n}=1\right)=\Phi\left(l^P_{(j^P+1)n}-\alpha^P_n X_n-\lambda_n \Delta X_n\right)-\Phi\left(l^P_{j^P n}-\alpha^P_n X_n-\lambda_n \Delta X_n\right), \tag{7}$$

where $j^P=0,...,M$; $l^P_{j^P n}$ is the threshold for purchasing at level j^P_n with $l^P_{0n}=-\infty$ and $l^P_{(M+1)n}=+\infty$; the vector of coefficients α^P_n measures the effect of the explanatory variables, and the vector λ_n measures the effect of the changing explanatory variables on purchasing. For notational convenience, we use $F^P_{j^P n}$ to denote the probability of purchasing at level j^P or $F^P_{j^P n}=P(z_{j^P n}=1)$.

2.3. Unified model

We assume that the random factors that affect intentions and purchasing are independently and identically distributed as bivariate normal with correlation ρ. The imperfect correlation results from unobservable factors that cause true intentions to be an imperfect representation of actual purchasing, even without systematic intention biases and even when true intentions do not change over time. In particular, there may be a fundamental difference between forming an intention to perform and achieving the related goal (Gollwitzer, 1999). In a purchasing context, the unobservable factors might include the product being out of stock (Bagozzi & Dholakia, 1999, 2006) or underestimated search costs.

When respondents report their true intentions, the joint probability that they equal j and that actual purchasing equals level j^P is given by:

$$P\left(y_{jn}=1,z_{j^P n}=1\right)=G\left(j,j^P\right)+G\left(j-1,j^P-1\right)-G\left(j,j^P-1\right)-G\left(j-1,j^P\right). \tag{8}$$

The function $G(j,j^P)$ denotes the cumulative probability distribution that the level of true intentions is less than or equal to j and that the actual purchasing level is less than or equal to j^P. To simplify the notation, we use $F^{*P}_{jj^P n}$ to denote the joint probability in Eq. (8).

Eq. (8) also includes the changes in true intentions over time that are caused by changing explanatory variables and the imperfect correlation between true intentions and purchasing. However, it does not allow for intention bias. We thus refer to it as the *unified model without intention bias*. When intentions bias is present, we instead follow Eq. (3) and obtain the joint probability that the respondent states an intention level j and purchases at level j^P:

$$P\left(y_{jn}=1,z_{j^P n}=1\right)=\pi_{jn}\left[\sum_{i=0}^{j} F^{*P}_{ij^P n}\right]+\left[1-\sum_{i=j}^{M}\pi_{in}\right]F^{*P}_{jj^P n}. \tag{9}$$

The first term in Eq. (9) is the joint probability that the respondent has independent intentions at level j and true intentions lower than or equal to j but purchases at level j^P. The second term is the joint probability that the respondent has true intentions at level j and independent intentions lower than or equal to j but purchases at level j^P. We thus call Eq. (9) the *unified model with intention bias*.

This unified model integrates systematic intention biases, changes in true intentions over time, and the imperfect correlation between true intentions and actual purchasing. It thus unites stated intentions and purchasing. Furthermore, in the unified model, the same covariate has different coefficients when it serves to explain intentions and purchasing. The log-likelihood function is thus given by:

$$\log L=\sum_{n,j,j^P} y_{jn} z_{j^P n}\log\left[P\left(y_{jn}=1,z_{j^P n}=1\right)\right] \tag{10}$$

At the heart of the unified model is a bivariate probit model. We use maximum likelihood to jointly estimate the parameters l_{jn}, α_n, $k_{jn}, \gamma_n, l^P_{jn}, \alpha^P_n, \lambda_n$, and ρ for all j. To account for respondent heterogeneity, we adopt the latent class approach that Kamakura and Russell (1989) recommended.

3. Purchase prediction using intentions data

Whereas the unified model describes the relationship between stated intentions and purchasing, firms are often interested in forecasting purchasing before gathering purchase data. To forecast purchasing based on stated intentions alone, we need a calibration sample, such as an historical sample including both intentions and purchase data, to calibrate the parameters $l^P_{jn}, \alpha^P_n, \lambda_n$ and ρ. We label such a sample the calibration sample (i.e., for which both intentions and purchase data are available), but the intention survey data constitute the prediction sample (i.e., only intention data are available).

When we calibrate reliable values for $l^P_{jn}, \alpha^P_n, \lambda_n$ and ρ we can calculate the probability that respondent n purchases at level j^P, conditional on the stated intention level j, using Bayes Law:

$$A_{jj^P n}=\Pr\left(z_{j^P n}=1\,|\,y_{jn}=1\right)=\frac{\Pr\left(y_{jn}=1,z_{j^P n}=1\right)}{\Pr\left(y_{jn}=1\right)}, \tag{11}$$

where $A_{jj^P n}$ denotes the conditional probability that the *nth* respondent purchases at the j^Pth level, conditional on her stated intention level j. We can obtain $\Pr(y_{jn}=1,z_{j^P n}=1)$ by calculating the joint probability of purchasing at the j^Pth level and stating the jth intention level, as defined in Eq. (9), using the known values of $l^P_{jn}, \alpha^P_n, \lambda_n$, and ρ that we derive from the prediction sample. To obtain $\Pr(y_{jn}=1)$, we calculate the probability of stating the jth intention level, as defined in Eq. (3), according to the prediction sample. Thus, the probability that the nth respondent purchases at the j^Pth level ($A_{j^P n}$) can be calculated as:

$$A_{j^P n}=\sum_{j=0}^{M}\left[A_{jj^P n}\Pr\left(y_{jn}=1\right)\right]. \tag{12}$$

When historical data are not available, there are alternative ways of obtaining estimates for $l^P_{jn}, \alpha^P_n, \lambda_n$ and ρ. For example, marketers could conduct a pilot study to survey intentions and purchasing from a smaller number of respondents. An alternative is to calibrate the values of these variables by applying the unified model to a closely related product for which both intentions and purchase data are available. If neither of these options is applicable, marketers can make simplified assumptions about the appropriate values for $l^P_{jn}, \alpha^P_n, \lambda_n$ and ρ.

4. Empirical application

4.1. Data description

We apply the model to two intention survey data sets. The first involves automobiles; the second pertains to personal computers. For the calibration samples, we used stated intentions collected from 2000 randomly selected households in the fourth quarter of 1988 for automobiles and from 3315 households in January 1986 for personal computers. We obtained actual purchase information from subsequent surveys. For

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Table 2
Descriptive statistics.

Variable name	Variable descriptions	Mean or percentage	
		Calibration sample	Prediction sample[a]
A. Automobile			
Number of observations		2000	1000
INTENTION 1	Intend to purchase automobile within 12 months	9.87%	9.54%
0	Do not intend to purchase automobile within a year	90.13%	90.46%
PURCHASE 1[a]	Purchase automobile within 12 months after survey	5.01%	5.13%[b]
0	Do not purchase automobile within a year after survey	94.99%	94.87%
MARRIED	Married couple	57.95%	55.32%
FEMALEEMPLOYED	Female is full-time or part-time employed	31.1%	29.4%
OCC1 — MANAGER, PROFESSIONAL	Household head occupation — manager, professional	23.01%	25.14%
OCC5 — CRAFT AND REPAIR	Household head occupation — craft and repair	7.0%	6.88%
OCC6 — OPERATOR AND LABOR	Household head occupation — operator and laborer	8.22%	8.53%
EDU	Education level of household head (0 = less than grade school; 1 = grade school; 2 = grad. grade school; …; 7 = post graduate university)	4.11	4.27
LIVE3 — MOBILE HOME	Type of residence — mobile home	6.13%	5.99%
LIVE4 — CONDOMINIUM	Type of residence — condominium	2.14%	2.06%
OWN1 — OWN HOME	Own home	7.58%	7.36%
INCOME	Income (1 = <10,000; 2 = 10,000–19,999; 3 = 20,000–29,999; 4 = 30,000–44,900)	2.86	2.71
YEAROFCAR	Years of car currently in household	2.84	2.99
B. Personal computer			
Number of observations		3315	1105
INTENTION 2	Intend to purchase PC within 6 months	7.52%	7.38%
1	Intend to purchase PC within 7 to 12 months	13.97%	15.26%
0	Do not intend to purchase PC within a year	78.51%	77.36%
PURCHASE 2	Purchase PC within 6 months after survey	6.69%	6.42%
1	Purchase PC within 7 to 12 months after survey	5.51%	5.67%
0	Do not purchase PC within a year after survey	87.80%	87.91%
NUMCARS	Number of cars	1.62	1.67
BABY	Family has children under 6 years-old	16.95%	16.54%
YOUNG	Age ≤30	31.78%	32.61%
EDUCATION	Householder education (0 = less than grade school; 1 = Grade school; 2 = Grad. grade school;…;7 = post graduate university)	4.19[b]	4.25
LGSIZE	Large size family with more than 6 members	0.093%	0.117%
NEW-HOUSEHOLD	Household's life cycle — new household	14.85%	14.37%
UPSCALE	Household's life cycle — upscale families	22.80%	21.46%
MIDAGE-NO KIDS	Household's life cycle — mid. aged without children	23.52%	22.65%
PROFESSIONAL	Householder occupation — professional	24.80%	25.37%
CLERICAL	Householder occupation — clerical	28.20%	29.61%
WORKING-HOURS	Number of working hours of householder	2.50	2.61
MALE-HEAD	Household head is male	79.44%	76.79%
WHITE-COLLAR	Household head is white-collar	34.65%	35.42%
INCOME	Household income	$38,868	$37,932
NEWCAR	Whether household purchases a car after the survey	7.4%	8.1%
HOME	Whether household changes the status of residence after the survey (from living with relatives to renting and from renting to owning)	3.2%	2.9%

[a] The purchase information for the prediction sample is used to validate predictive accuracy. In applying the unified model to the focal prediction sample, we assume this information is not available.

automobiles, the purchase data were obtained one year after intentions were measured; for personal computers, the purchase data were separately obtained 6 and 12 months after intentions were measured.

For the automobile data, we define the intention level j (purchase level j^P) as

$$j\left(j^P\right) = \begin{cases} 1, & \text{if the nth respondent intends to (actually) purchase an automobile within 12 months} \\ 0, & \text{if no purchase is intended (actually occurs) within 12 months.} \end{cases}$$

For the personal computer data, we construct the intention level j and purchase level j^P as follows[4]:

$$j\left(j^P\right) = \begin{cases} 2, & \text{if the nth respondent intends to (actually) purchase a personal computer within 6 months} \\ 1, & \text{if the nth respondent intends to (actually) purchase a personal computer within 7–12 months} \\ 0, & \text{if no purchase is intended (actuallyoccurs) within 12 months.} \end{cases}$$

[4] The automobile purchase survey asked respondents whether they purchased an automobile within the year. Thus we have binary purchase information for two categories: bought within a year or did not. For the personal computer data, the purchase information is available for three levels, so our model included three purchase levels. This aggregation solely reflects the data limitations and is not required for the application of our unified model.

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Table 3
Comparison of data fit (based on calibration sample).

A. Automobile

	(1) Morrison's Model	(2) Bemmaor's Model	(3) Ignore purchase information	(4) Ignore intentions bias ($\pi_{jn}=0$ for all j)	(6) Ignore imperfect correlation ($\rho=0$)	(7) Unified model with homogeneous respondents	(8) Unified model with heterogeneous respondents
Model selection							
−Log-L value	1745.1	NA	890.4	1694.5	1667.0	1632.0	1604.9
AIC	1749.1		903.4	1717.5	1691.0	1657.0	1634.9
BIC	1760.3		939.8	1781.9	1758.2	1727.0	1726.5
CP[a]							
Intenders	0.795	0.798	0.802	0.831	0.855	0.935	0.939
Nonintenders	0.867	0.879	0.837	0.852	0.905	0.966	0.968
SSR							
Intenders	0.475	0.439	0.385	0.326	0.190	0.122	0.112
Nonintenders	0.519	0.483	0.378	0.334	0.212	0.174	0.151

B. Personal computer

	(1) Morrison's Model	(2) Bemmaor's Model	(3) Ignore purchase information	(4) Ignore intentions bias ($\pi_{jn}=0$ for all j)	(5) Ignore true intentions shift ($\lambda_n=0$)	(6) Ignore imperfect correlation ($\rho=0$)	(7) Unified model with homogeneous respondents	(8) Unified model with heterogeneous respondents
Model selection								
−Log-L value	2255.6	NA	1046.1	2139.1	2043.0	2100.6	2081.8	2120.1
AIC	2259.6		1062.1	2162.1	2072.0	2130.6	2112.8	2141.1
BIC	2271.8		1110.9	2297.1	2241.6	2222.2	2207.4	2199.1
CP								
Intenders 1	0.680	0.798	0.823	0.840	0.864	0.867	0.922	0.927
Intenders 2	0.731	0.842	0.820	0.799	0.850	0.860	0.935	0.939
Nonintenders	0.726	0.801	0.838	0.881	0.924	0.938	0.964	0.968
SSR								
Intenders 1	0.460	0.432	0.439	0.364	0.272	0.176	0.136	0.134
Intenders 2	0.477	0.429	0.421	0.375	0.283	0.184	0.139	0.135
Nonintenders	0.485	0.456	0.455	0.374	0.284	0.185	0.140	0.137

[a] CP is the number of correct predictions; SSR is the sum of squared residuals. We report these statistics for both respondents who reported an intention to buy the product (intenders) and those who reported no intention to buy the product (nonintenders).

We follow Morwitz and Schmittlein (1992) and treat timed purchase intentions and purchasing levels as ordered choices. As long as the intentions and purchase levels are discrete and ordered, our model is applicable.

Our data provide extensive demographic information that includes household size, annual household income, age of the head of household, marital status, home ownership, household stage of life, occupation, education of the head of household, race, number of cars owned, regional dummy variables, and ownership of a cellular phone. For the automobile data, these demographic variables were measured once at the time of the survey. However, for the personal computer data, the demographic information were collected during the intentions survey and during the purchase measures. Of these variables, we noted that both NEWCAR (i.e., whether the subject had bought a car) and HOME (i.e., residence status) changed between the time of the initial survey and the time of purchase. We can therefore analyze the impact of changes in these two variables to demonstrate how changes in explanatory variables may be associated with changes in true intentions over time.

For the prediction samples, we used stated intentions, which were collected from 1000 households in the fourth quarter of 1989 for the automobile data and from 1105 households collected in January 1987 for the personal computer data. The definition of the intention levels is the same as that of the calibration sample.

Table 2 contains all the variables used in the estimation and descriptive statistics for both the calibration and prediction samples. When we compare the percentage of respondents who stated their intention to buy with the corresponding percentage who actually purchased, we find that respondents exaggerated their intentions to buy in both the calibration and prediction samples. For example, in the personal computer prediction sample, 15.3% of the respondents stated they would purchase a computer within a year, but only 5.7% did so.

4.2. Model comparison

We use the calibration sample to estimate eight models to examine whether adding purchase information and considering various discrepancies helps to explain the relationship between stated intentions and purchasing. Models 1 and 2 represent Morrison's (1979) and Bemmaor's (1995) models, which can only predict the aggregate probabilities of a binary purchase–no purchase situation. Therefore, we treat buying within 12 months as a purchase and all other cases as nonpurchases for the personal computer data. Model 3 is our unified model that ignores purchase information, similar to recent disaggregated intention models (*e.g.*, Hsiao & Sun, 1999; Young et al., 1998). Models 4–6 are our unified models that ignore systematic intention biases ($\pi_{jn}=0$ for all j), changes in true intentions over time ($\lambda_n=0$), and the imperfect correlation between true intentions and purchasing ($\rho=0$), respectively; they also lack unobserved heterogeneity. Model 7 is our unified model

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with homogeneous respondents. Finally, Model 8, our proposed model, adds unobserved heterogeneity to Model 7. Models 4–6 represent nested variations of our proposed model. We lack information on changes in the explanatory variables for the automobile data, and therefore, we do not estimate Model 5 for this product category.

We determine the number of segments empirically from the data and find that three segments for the automobile and two segments for the personal computer data provide the best description. In Table 3, we compare log-likelihood values, Akaike information criterion (AIC), Bayesian information criterion (BIC), number of correct predictions (CP), and the sum of squared residuals (SSR) for the eight models. Our comparisons of CP and SSR show that the unified models (Models 7 and 8) significantly outperform existing aggregate intention models (Model 1 and 2) and the disaggregate intention model (Model 3). All model fit statistics indicate that the unified models also fit better than Models 4–6; this finding suggests that it is important to consider all three discrepancies to model the relationship between intentions and purchasing.

Using a comparison of the model fit statistics for Models 3–7, we note that the greatest improvement in model fit comes from adding the purchase model (Eqs. (5)–(7), as in the unified model) and allowing for systematic intention bias (i.e., allowing π_{jn} to be nonzero for all j). The next best improvement comes from incorporating changes in true intentions over time (i.e., allowing λ_n to be nonzero) and then incorporating the imperfect correlation between intentions and purchasing (i.e., allowing ρ to be nonzero). Adding unobserved heterogeneity (Model 8) further improves model fit, but to a lesser extent than do the other model components.

It is also interesting to compare the percentage improvements across product categories. We find that intention bias is more important for the personal computer data (*e.g.*, BIC improves by 3.90%, from 2297.1 to 2207.4) than it is for the automobile data (BIC improves by 3.10%, from 1781.9 to 1727.0). This difference is not surprising; when the data were gathered, automobiles were utilitarian products, and personal computers represented more socially desirable products. Incorporating the imperfect correlation between intentions and purchasing produces a more improved fit more for the automobile data (BIC improves by 1.77%, from 1758.2 to 1727.0) than it does for the personal computer data (BIC improves by 0.67%, from 2222.2 to 2207.4). We posit in this case that, because automobiles are more expensive than personal computers, the discrepancy between stating or forming an intention and fulfilling it should be greater. Thus, it is more important to take into account the imperfect correlation between intentions and purchasing for automobiles than it is for personal computers.

4.3. Parameter estimates

In Table 4, we report the parameter estimates and their standard errors obtained from our proposed unified models (Model 7 and 8), that is estimated based on the calibration sample. In Model 8, for the automobile data, the latent class approach classifies the respondents approximately equally into three segments. For the personal computer data, two-thirds of the respondents enter the first segment, and the rest constitute the second segment. Across segments, most coefficients differ in magnitude and significance level, but not direction. To simplify our analysis, we focus on Model 7 (unified model with homogeneous respondents) to discuss the parameter estimates.

We first discuss the coefficients of the variables included in the intention equation (second column, Table 4). In the automobile data, the respondents who are married (−1.70), whose household heads are employed as craftsmen and repairmen (−0.48) or as operators and laborers (−0.32), or who live in mobile homes (−0.73) expressed lower intentions to purchase. These categories suggest that the respondents have less discretionary income, so they may be less likely to make a new purchase or replace their current automobiles. However, households that include an employed woman (0.13) or white-collar employee (0.29), that own a house (0.16) or a condominium (1.06), and that earn high incomes (0.18) express higher intentions to buy a car, possibly because they are wealthier. Consistent with Bayus and Gupta (1992), we find that households that have owned their current car longer also have higher intentions to buy, presumably to replace their old car.

When our data were collected, personal computers were relatively new. Their penetration was low, and learning how to use them required significant time. These factors may explain our finding that having babies (−0.11) and working long hours (−0.03) appear to be associated with lower intentions to purchase a personal computer. New households (−0.28) also indicate lower intentions, perhaps because of the financial pressures associated with starting a family. In contrast, the number of cars owned (0.07), a professional or clerical job (0.12), high income (0.23), and owning a cellular phone (0.31) are associated with increased intentions; these respondents tend to be better educated, wealthier, and more likely to use a computer at work. We also find that households with a male-head (0.26) or white-collar employment (0.07) express higher intentions to buy a computer. Large families (0.34) are also more likely to intend to buy a computer, perhaps because of the diverse needs of the different family members. Finally, the older the car owned by the household, the higher its intention to buy a personal computer (0.12). It is possible that families who recently replaced their cars are more financially constrained, which may lower their intentions to buy a personal computer.

The coefficients in the purchase equations have the same signs as their counterparts in the intention equations; however, they vary in magnitude with regard to their influence on intentions and purchasing. We also notice that the difference is smaller for automobiles than for personal computers. The many differences between automobiles and computers suggest a variety of possible reasons for this dissimilarity, but one key possibility is that, at the time the data were collected, more consumers had experience with automobiles than with personal computers. Prior research has shown that the effect of measuring intentions on behavior increases for those with less product experience (Morwitz et al., 1993); this distinction may be particularly significant for the difference we observed.

We next examine the coefficients of the variables that explain the probability of stating biased intentions. For both products, education is estimated to have a negative impact on the probability of stating biased intentions (−0.20 automobile, −0.33 personal computer); that is, more educated respondents should provide more accurate intentions. This estimation is consistent with previous studies that showed that the tendency to put minimal effort into responses is greatest among respondents with the lowest cognitive skills, as measured by educational attainment (*e.g.*, Krosnick et al., 2002). It is possible that more educated respondents can better understand the question and therefore formulate their answers more accurately.

Using these estimated coefficients, we calculate the average probability of providing biased intentions. For the personal computer data, π_1 and π_2 are 3.91 and 13.25, respectively, such that on average there is a 3.91% probability of respondents stating that they intend to buy a computer within 6 months even when their true intention is to buy within 7 to 12 months or not at all. There is also a 13.25% chance of expressing the intention to buy within 7 to 12 months, but the respondent's true intention is not to buy within the year. Similarly, respondents have an average probability of 4.78% of overstating their intentions to purchase an automobile. Thus, respondents are more likely to overstate their purchase intentions for personal computers than for automobiles. This finding is consistent with existing literature that indicates that respondents often

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Table 4
Parameter estimates (based on calibration sample).

A. Automobile

Variables	(7) Unified model with homogeneous respondents	(8) Unified model with heterogeneous respondents		
		Segment 1 0.34(0.11)	Segment 2 0.29(0.08)	Segment 3 0.37
Intention equation				
l_1 THRESHOLD1[b]	0.55(0.23)*	1.32(0.34)*	0.81(0.32)*	0.68(0.35)*
$-\alpha$ MARRIED	−1.70(0.62)*	−1.02(0.23)*	−1.70(0.54)*	−1.61(0.44)*
FEMALEEMPLOYED	0.13(0.08)*	0.20(0.15)	0.16(0.14)	0.20(0.19)
OCC1 — MANAGER, PROFESSIONAL	0.29(0.11)*	0.14(0.17)	0.25(0.17)	0.21(0.17)
OCC5 — CRAFT AND REPAIR	−0.48(0.22)*	−0.25(0.34)	−0.50(0.20)*	−0.40(0.38)
OCC6 — OPERATOR AND LABOR	−0.32(0.09)*	−0.41(0.11)*	−0.28(0.05)*	−0.29(0.09)*
LIVE3 — MOBILE HOME	−0.73(0.26)*	−0.72(0.26)*	−0.70(0.43)	−0.71(0.49)
LIVE4 — CONDOMINIUM	1.06(0.29)*	1.52(0.32)*	0.90(0.32)*	0.83(0.38)*
OWN1 — OWN HOME	0.16(0.07)*	0.10(0.13)	0.14(0.05)*	0.19(0.07)*
INCOME	0.18(0.05)*	0.32(0.11)*	0.18(0.21)	0.15(0.12)
YEAROFCAR	0.12(0.09)*	0.13(0.10)	0.12(0.05)*	0.10(0.13)
Intention bias				
k_1 THRESHOLD1	−2.41(0.79)*	−1.30(0.76)	−2.24(0.67)*	−2.17(0.56)*
$-\gamma$ EDU	−0.20(0.05)*	−0.16(0.03)*	−0.20(0.07)*	−0.29(0.13)*
Purchase equation				
l_1^P THRESHOLD1	0.90(0.23)*	0.93(0.37)*	0.25(0.35)	0.82(0.34)*
$-\alpha^P$ MARITAL1	−1.77(0.62)*	−1.05(0.52)*	−1.30(0.39)*	−1.75(0.42)*
FEMPL	0.14(0.06)*	0.19(0.09)*	0.92(0.13)*	0.15(0.10)
OCC1	0.32(0.15)*	0.31(0.13)*	0.43(0.16)*	0.30(0.11)*
OCC5	−0.49(0.18)*	−0.49(0.31)	−0.23(0.08)*	−0.48(0.17)*
OCC6	−0.31(0.11)*	−0.29(0.22)	−0.26(0.11)*	−0.32(0.18)
LIVE3	0.71(0.22)*	0.92(0.43)*	0.53(0.26)*	0.71(0.24)*
LIVE4	1.07(0.33)*	1.23(0.65)	1.03(0.29)*	1.06(0.30)*
OWN1	−0.12(0.08)	−0.21(0.07)*	−0.24(0.08)*	−0.16(0.10)
INCOME	0.18(0.08)*	0.19(0.11)	0.03(0.21)	0.17(0.23)
YEAR	0.14(0.12)	0.10(0.20)	0.021(0.22)	0.11(0.22)
Correlation				
ρ^c	0.73(20.9)	0.79(19.0)	0.71(9.95)	0.66(7.43)

B. Personal computer

Variables	(7) Unified model with homogeneous respondents	(8) Unified model with heterogeneous respondents	
		Segment 1 0.68(0.21)	Segment 2 0.32
Intention equation			
l_2 THRESHOLD1[b]	3.46(0.12)*	3.31(0.22)*	3.51(0.21)*
l_1 THRESHOLD1	1.83(0.26)*	1.75(0.36)*	1.90(0.23)*
$-\alpha$ NUMCARS	0.07(0.08)	0.05(0.02)*	0.09(0.02)*
BABY	−0.11(0.06)	−0.30(0.06)*	−0.34(0.05)*
LGSIZE	0.34(0.09)*	0.33(0.12)*	0.35(0.13)*
NEW-HOUSEH.	−0.28(0.10)*	−0.22(0.10)*	−0.30(0.15)*
PROFESSIONAL	0.12(0.03)*	0.11(0.03)*	0.13(0.02)*
WORKING-HOUR	−0.03(0.01)*	−0.03(0.02)	−0.04(0.02)
MALE-HEAD	0.26(0.12)*	0.22(0.06)*	0.29(0.10)*
WHITE-COLLAR	0.07(0.02)*	0.07(0.02)*	0.06(0.04)
INCOME	0.23(0.09)*	0.18(0.07)*	0.24(0.06)*
CELLULAR	0.31(0.12)*	0.30(0.12)*	0.29(0.13)*
Intention bias			
k_2 THRESHOLD2	−0.53(0.59)	−0.45(0.32)	−0.99(0.43)*
k_1 THRESHOLD1	−1.35(0.92)	−1.35(0.87)	−1.64(0.94)
$-\gamma$ EDUCATION	−0.33(0.08)*	−0.30(0.15)*	−0.34(0.14)*
Purchase equation			
l_2^P THRESHOLD2	1.8430.52)*	2.04(0.32)*	1.93(0.49)*
l_1^P THRESHOLD1	1.54(0.86)*	1.45(0.45)*	1.64(0.68)*
$-\alpha^P$ NUMCARS	0.06(0.02)*	0.05(0.03)	0.07(0.02)*
BABY	−0.33(0.08)*	−0.21(0.12)	−0.25(0.13)*
LGSIZE	0.31(0.09)*	0.42(0.07)*	0.27(0.08)*
NEW-HOUSEH.	−0.26(0.12)*	−0.32(0.11)*	−0.24(0.09)*
PROFESSIONAL	0.09(0.03)*	0.13(0.04)*	0.11(0.05)*
WORKING-HOUR	−0.03(0.01)*	−0.05(0.01)*	−0.04(0.01)*
MALE-HEAD	0.21(0.10)*	0.32(0.112)*	0.23(0.13)
WHITE-COLLAR	0.07(0.03)*	0.11(0.09)	0.10(0.03)*
INCOME	0.20(0.09)*	0.44(0.13)*	0.21(0.12)
CELLULAR	0.29(0.08)*	0.22(0.10)*	0.25(0.07)*

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Table 4 (*continued*)

B. Personal Computer			
Variables	(7) Unified model with homogeneous respondents	(8) Unified model with heterogeneous respondents	
		Segment 1 0.68(0.21)	Segment 2 0.32
Purchase equation			
$-\lambda$ NEWCAR	−0.02(0.005)*	−0.03(0.005)*	−0.03(0.006)*
HOME	−0.03(0.008)*	−0.04(0.008)*	−0.04(0.007)*
Correlation ρ^c	0.54(4.99)	0.57(6.10)	0.57(5.56)

[a]Standard errors reported in parentheses.
[b]We can estimate all thresholds because we do not have a constant term in the utility functions.
[c]The Wald test is reported for P.
*Significant at 0.05 level.

exaggerate their future demand for socially desirable, new, high-tech products (Hsiao et al., 2002).

In the personal computer data, we find that buying a car within a year of the survey and changing residential status decreases the probability of acquiring a personal computer in the near future ($\lambda = -0.021$ for NEWCAR, -0.033 for HOME). We suggest that this effect appears because purchasing a car and/or spending more money on housing costs and moving reduces a household's disposable income; this decrease is likely to lower the household's propensity to buy another expensive product. However, these variables are the only ones in our data that changed over the course of a year and had significant impacts on purchasing. The inclusion of product- and promotion-related variables could enhance these results.

The estimated ρ for the automobile data is 0.742, and for personal computers it is 0.536. The Wald test shows that both are significant; therefore, intentions and purchasing are positively but not perfectly correlated. At the time of the surveys, automobiles were a mature product category, and personal computers were a fast-growing, new category. Therefore, it is not surprising to find a higher correlation between true intentions and purchasing for automobiles than for personal computers.

4.4. Prediction with historical purchase data

After estimating the unified model using the calibration data and obtaining estimates of $l_{jn}^P, \alpha_n^P, \lambda_n$, and ρ, we apply the intention bias model to the prediction sample, which contains only intention data, to obtain new estimates of l_{jn}, α_n, and λ_n. We then calculate individual purchase probabilities according to Eq. (12). In Table 5, Panel A, we report the CP and SSR; in Panel B, we compare the model predictions of the unified models (Models 7 and 8) and existing models (Models 1–3) with actual observations in a confusion matrix. Models 1 and 2 offer only aggregate probabilities of the binary purchase–no purchase choice at each intention level, and therefore, we multiply the total number of respondents by the predicted probabilities to obtain the estimated number of purchases. In contrast, for the disaggregate models, we can predict purchase probability for each respondent and simply count the quantity that is predicted to purchase.

All the prediction criteria show that the proposed unified models (Models 7 and 8) predict actual purchasing more accurately than do the other models. For example, among the 82 respondents who stated an intention to purchase a personal computer within 6 months, Models 1 and 2 predict that 61% and 64% of the respondents, or 50 and 52 respondents, respectively, will purchase within a year. In reality, 59 respondents purchased a computer. Furthermore, the unified Model 7, with its separate predictions, anticipates that 53 respondents would purchase within 6 months, 9 would purchase within a year, and 20 would not purchase. In contrast, the disaggregate Model 3 predicts values of 66, 5, and 11 respondents, respectively, for these three time periods. The actual numbers—51, 8, and 23 respondents—demonstrate that the unified model significantly improves the accuracy of the prediction compared to existing models. By recognizing the various discrepancies between intentions and purchasing and allowing for a connection between intentions and purchasing, our unified model provides more accurate purchasing predictions. Model 8 provides even greater prediction accuracy by incorporating unobserved heterogeneity.

4.5. Prediction without historical purchase data

Thus far we have only considered situations in which we have an historical calibration sample with purchase information. To demonstrate the usefulness of our unified model when historical data are not available and a pilot study is not feasible, we estimated alternative versions of our unified models (Models 7′ and 8′), in which we assume $l_{jn}^P = l_{jn}$, $\alpha_n^P = \alpha_n$, $\lambda_n = 0$, and $\rho = 0.53$ for all respondents. By making $\alpha^P = \alpha$ and $\lambda = 0$, we assume that the explanatory variables affect intentions and purchasing in the same way and that true intentions do not change over time. Our assumption that $\rho = 0.53$ is based on Sheppard, Hartwick and Warshaw's (1988) meta-analysis of the applications of Fishbein and Ajzen's Model, which showed that the frequency-weighted average correlation for the intention–behavior relationship is 0.53.[5] We again compare CP, SSR, and the predicted number of purchases across models; the predictive accuracy of Models 7′ and 8′ is still better than that of Models 1–3. However, they perform worse than Models 7 and 8. Thus, even with intention data alone, our model still outperforms existing intentions models if marketers make reasonable assumptions about the parameter values.

[5] Sheppard et al. (1988) find substantial variation in the correlations, so we also examined Models 7′ and 8′ with ρ equal to 0.15 and 0.92 (i.e., 95% confidence limits of the average correlation). We estimated another version of the models with $\rho = 0.76$, based on the observed intention–purchase correlation in a similar meta-analysis for durable goods (Morwitz, Steckel, & Gupta, 2007). We report the prediction results for $\rho = 0.53$ because this value gives the best prediction for both product categories. The choice of the value for ρ is *ex post*; we leave to additional research the question of how to choose the best values for l_{jn}^P, α_n^P, and λ_n when no purchase data are available.

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Table 5

A. Comparing prediction accuracy

Automobile

	(1) Morrison's Model	(2) Bemmaor's Model	(3) Existing disaggregate model	With historical purchase data		Without historical purchase data	
				(7) Unified model with homogeneous respondents	(8) Unified model with heterogeneous respondents	(7)′ Unified model with homogeneous respondents	(8)′ Unified model with heterogeneous respondents
CP							
Intenders	0.688	0.736	0.802	0.912	0.922	0.917	0.921
Nonintenders	0.856	0.862	0.821	0.933	0.939	0.902	0.911
SSR							
Intenders	0.474	0.437	0.443	0.143	0.149	0.185	0.180
Nonintenders	0.485	0.447	0.473	0.190	0.182	0.219	0.196

Personal computer

	(1) Morrison's Model	(2) Bemmaor's Model	(3) Existing aggregate model	With historical purchase data		Without historical purchase data	
				(7) Unified model with homogeneous respondents	(8) Unified model with heterogeneous respondents	(7)′ Unified model with homogeneous respondents	(8)′ Unified model with heterogeneous respondents
CP							
Intenders 1	0.698	0.775	0.790	0.925	0.931	0.902	0.914
Intenders 2	0.702	0.783	0.804	0.934	0.944	0.854	0.898
Nonintenders	0.732	0.824	0.825	0.938	0.945	0.891	0.907
SSR							
Intenders 1	0.440	0.429	0.461	0.161	0.154	0.175	0.175
Intenders 2	0.463	0.425	0.468	0.165	0.156	0.183	0.180
Nonintenders	0.472	0.453	0.465	0.171	0.162	0.183	0.183

B. Comparing predictions with actual observations (confusion matrix)

Automobile

Intentions (total)	Purchases in sample		Derived purchases conditional on stated intentions											
	1	0												
1 (95)[a]	42[b]	53	40.5% (38)	54.8% (52)	47	48	43	52	43	52	44	51	43	52
0 (905)	9	896	12.6% (114)	4.79% (43)	16	889	11	894	10	895	12	893	10	895

Personal computer

Intentions (total)	Purchases in sample			Derived purchases conditional on stated intentions																
	2	1	0																	
1 (82)	51	8	23	61% (50)	64% (52)	66	5	11	53	9	20	52	9	21	54	8	18	*54*	*8*	*20*
2 (168)	11	53	104	35% (59)	37% (62)	16	59	93	10	55	103	10	55	103	13	57	98	*9*	*52*	*107*
0 (855)	10	3	842	3.4% (29)	5.3% (45)	14	5	836	12	3	840	*11*	*3*	*841*	13	5	837	*13*	*5*	*837*

[a] 95 is the total number of respondents who reported intentions Level 1.

[b] 42 indicates that out of the 95 respondents stating intentions Level 1 (intend to purchase within 12 months), 42 actually made a purchase within 12 months. This figure is the actual number of purchases in the prediction sample. This information is not used for estimation and prediction. It is only used as a benchmark for examining the predictive accuracy of the different models.

5. General discussion

We have proposed a unified model that takes into account systematic intention biases, changes in true intentions over time, and the imperfect correlation between true intentions and actual purchasing. It also unifies stated intentions and purchasing. By applying the proposed unified model to survey-based intention data for automobiles and personal computers, we demonstrated that the combination of stated intentions and actual purchasing allows the proposed model to provide a better description of their relationship than have previous statistical intention models. It also provides more accurate individual and multilevel forecasts of actual purchase probabilities. Our unified model works better with some purchase information, and we therefore recommend a pilot study or investigation of a closely related product to obtain parameter estimates for newly introduced products. However, if these tactics are not possible, we can nevertheless recommend the use of our model with reasonable assumptions about the parameter values.

However, our model is also limited by several simplifying assumptions, which open avenues for further research. First, a more comprehensive model can be developed to take into account additional kinds of intention biases, such as the one-sided intention bias that Hsiao and Sun (1999) documented. Other extensions could consider unordered choices. Furthermore, our statistical model does not capture the response process, nor does it provide an accurate description of actual respondent behavior, despite its strong fit with the data. To avoid modeling bias, which affects most statistical approaches, structured models could explicitly consider the response process. Second, more flexible forms of choice models would accommodate marketing mix variables. Third, our cross-sectional study takes into account changes in true intentions over time with a single measure of stated intentions and a single-item measure of intentions. The model should be extended to incorporate multi-item intention measures and measures that span multiple time periods. For example, with multiple measures of consumers' latent true intentions, latent trait or itemized response, models could reveal the relationship

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between intentions and purchasing (Bagozzi et al., 1999). Fourth, because our primary goal was to forecast purchase rather than to demonstrate the mere measurement effect, we studied the most common situation (i.e., only information from survey respondents is available) and used a statistical approach to incorporate the mere measurement effect. A more accurate measure of the mere measurement effect demands information from respondents who did not participate in the survey (Chandon, Morwitz & Reinartz, 2004; Chandon et al., 2005; Fitzsimons & Morwitz, 1996; Louviere et al., 1999; Morwitz & Fitzsimons, 2004; Morwitz et al., 1993). Fifth, researchers should apply the unified model to multiple product categories to determine how the relationships between stated intentions and purchasing vary across product categories. Similarly, it would be interesting to investigate whether the relationship differs when the customers buy "new" products in an existing product category versus when they purchase a genuinely new product category.

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