A Varying-Parameter Averaging Model of On-Line Brand Evaluations

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Consumer evaluations of new brands evolve over time as information is acquired. We conceptualize the extent to which evaluations are updated in terms of the weight given to new information during information integration. Based on information processing theory, we derive hypotheses regarding the weights given to new information under different processing ability conditions. We then develop a varying-parameter averaging model that captures the hypothesized moderating effects of processing ability (i.e., time pressure and knowledge) and also takes into account order effects. Scale values and weights for information items are derived by estimating the model using continuous evaluations obtained in a process-tracing experiment that allows subjects to access information that they desire in any order. Results from model estimation support the hypothesis that compared with prior evaluations new information plays a larger role in evaluations of high (vs. low) ability subjects. Estimating order effects on weights when order is endogenous, we find a recency effect such that information seen later is given a greater weight than information seen earlier. However, this recency effect is reduced as category knowledge increases. We discuss the theoretical and methodological contributions of this research.

Linda wishes to purchase a car. Her best friend recently bought a Honda Accord and recommends it highly. Linda therefore decides to look closely at the Accord based on the three attributes that she considers most important: safety, acceleration, and handling. She first looks up the Honda World Wide Web site for safety information and is impressed with the car's safety record. She then turns to *Consumer Reports* and finds that the Accord fares lower on acceleration than some other models in its class. Linda therefore adjusts her prior evaluation of the Accord downward. She also discovers that the Accord is rated the best on handling by *Consumer Reports* and revises her evaluation upward. Linda's final evaluation is extremely positive. She therefore decides to buy the car.

This hypothetical example suggests that formation of brand evaluations is often characterized by an anchor-and-adjust process based on sequential information access. Yet, persuasion research has generally studied attitude change by comparing attitude toward an object (e.g., a brand) before versus after exposure to information about the object (e.g., an ad). Other research has examined repeated judgments as information is accessed. However, the order in which the information is accessed by subjects has been imposed by the researcher (e.g., Hogarth and Einhorn 1992). This article addresses these limitations by using a continuous evaluation assessment procedure to study how brand evaluations evolve as subjects acquire information that they desire in the order that they choose. The continuous assessment procedure simulates a situation in which consumers have an impression formation goal and therefore form brand evaluations on-line, as they acquire information (Hastie and Park 1986; Lichtenstein and Srull 1987).

Consistent with information integration theory (Anderson 1971, 1981), we conceptualize the evaluation formation process as a function of prior evaluation and new information. In other words, consumers are likely to anchor their brand evaluations on prior evaluations and ad-

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just these evaluations based on new information (cf. Einhorn and Hogarth 1985; Lopes 1982). When new information is acquired, evaluations may stay the same, become more favorable, or become less favorable. Lopes (1982, p. 2) describes such a serial adjustment process as one in which ''information is scanned, items are selected for processing, scale values are assessed, and adjustments are made (at least after the first step) to an interim quantity that summarizes the results from already-processed information.'' In the present research, we examine how consumers' ability to process information affects the extent to which prior evaluation, which serves as an ''anchor,'' is adjusted in the face of new information acquired in the order desired by the consumer. We do this by assuming that an averaging process underlies evaluation formation; conceptualizing the extent of adjustment to prior evaluation as the ''weight'' given to new information; and estimating weights given to prior evaluation and new information acquired at different stages. Comparing the weights given to new information at different stages of information acquisition provides insight into order effects when order is endogenous.

WEIGHTING PRIOR EVALUATION VERSUS NEW INFORMATION

Current brand evaluation is viewed as a function of prior evaluation and new information. Different model forms such as additive and multiplicative can be used to represent this process (see Lynch [1985] for a review). We assume an averaging model because previous research has documented that an averaging process underlies attitude formation (Anderson 1981; Lopes 1982). Therefore, the weights given to prior evaluation and new information are inversely related—the greater the weight given to new information, the lower the weight given to prior evaluation. An important question concerns the conditions under which prior evaluation has a greater impact on current attitude than does new information (Eagly 1992; Eagly and Chaiken 1993). Ability to process information has been implicated as one such moderator.

The effect of ability to process information on adjustments made for new information has been extensively studied by Gilbert (Gilbert, Krull, and Pelham [1988]; Gilbert, Pelham, and Krull [1988]; see Gilbert [1989] for a review). Gilbert suggests that the judgment process consists of three sequential processes: categorization, characterization, and correction. Correction is considered more effortful than the other two processes, which are thought to occur automatically. Thus, anything that reduces the resources that are available to process information inhibits the correction phase but not the earlier phases.

We draw on this research and translate it to the evaluation formation domain. We consider the process of utilizing new information to update prior evaluations as akin to the process of correction described by Gilbert. Therefore, factors that reduce ability to process information will result in lower weight being given to new information and greater weight being given to prior evaluation. In Greenwald's (1968) terminology, low ability subjects accept positive information but their uncertainty results in lower levels of intensity in their cognitive responses. Two factors shown to affect information processing ability are time pressure (Wright and Weitz 1977) and knowledge (Chaiken, Liberman, and Eagly 1989). Time pressure can be considered a situational variable whereas knowledge is an individual difference variable

Consumers with an impression formation goal who are under high time pressure to evaluate a new brand will acquire some information to form an initial evaluation and will tend to stick to this evaluation rather than to correct prior evaluations with new information. They are less likely to adjust their evaluations (the anchor) significantly even if new information is acquired (Sanbonmatsu and Fazio 1990; Tversky and Kahneman 1974). When not under time pressure, consumers are more likely to deliberate on their evaluations, which are more likely to be updated with each item of new information (Liberman, de La Hoz, and Chaiken 1988).

Past research has also identified knowledge as an important determinant of persuasion (Maheswaran and Sternthal 1990). As Eagly and Chaiken (1993, p. 242) state in their discussion on applications of information integration theory to attitude change, ''The weight of the initial attitude would typically be identified with recipient factors such as . . . amount of previous knowledge.'' Consumers with little relevant knowledge about the product category are likely to lack awareness of which information items are important and also of how much to weight different information items in evaluating a new brand in the product category. This uncertainty in information acquisition and weighting is likely to make low knowledge consumers resistant to updating prior evaluations, thus reducing the weight that these consumers give to new information compared with prior evaluations. In contrast, consumers with higher levels of knowledge about the product category know the information items that must be acquired (Alba and Hutchinson 1987; Johnson and Russo 1984) and also know the relative weights to be applied to different information items in evaluating a new brand. Category knowledge enables high knowledge consumers to update their evaluations of a new brand more easily as new information is obtained. Therefore, we hypothesize that:

H1a: New information (prior evaluation) is likely to affect the brand evaluations of consumers under no time pressure conditions more (less) than the brand evaluations of consumers under high time pressure conditions.

H1b: New information (prior evaluation) is likely to affect brand evaluations more (less) under high category knowledge conditions compared with low category knowledge conditions.

ORDER EFFECTS IN BRAND EVALUATIONS

Hypothesis 1 contrasts the weight given to new information with that given to prior evaluation. Note that these weights are inversely related given the assumption of averaging. Conditions resulting in less weight given to new information (i.e., high time pressure and low knowledge) are also likely to result in less weight given to information acquired later (vs. earlier) in information acquisition. This is because information acquired early is used to form an initial evaluation of a new brand whereas information acquired later is not utilized to update prior evaluations. Below we draw on research concerning order effects to provide further support for this notion.

The stage at which information is acquired (early vs. later in the sequence of total information acquired) is likely to moderate the weight given to the information (Anderson 1965; Anderson and Hubert 1963; Jones and Goethals 1972). When an impression formation goal is in place and people form on-line brand evaluations, they are likely to weight later information more heavily than earlier information. This recency effect is attributed to subjects being forced to attend to later information and has been demonstrated using continuous judgment tasks where subjects respond in a ''step-by-step'' mode (cf. Hogarth and Einhorn 1992; Stewart 1965). As Schwarz, Strack, and Mai (1991) suggest, there is an implied demand to attend to new information and revise opinions.

However, when subjects lack ability to process information, they will not be able to integrate later information into an overall judgment even under forced attention conditions. This is especially likely when judgments are made under high time pressure (Kruglanski and Freund 1983) because uncertainty about the weight to be applied to information items may increase as more information is acquired and time pressure increases. Thus, under these conditions, later information items may not be integrated into prior evaluations. Recency effects may therefore not be observed. Based on the preceding discussion, we hypothesize that for on-line evaluations:

H2a: In general, recency effects are likely to occur in evaluation formation such that later information items are given a greater weight in integration than are earlier items.

H2b: Recency effects are less likely to occur under conditions of high time pressure compared with low time pressure.

Category knowledge can affect ability to select, interpret and integrate new information and is therefore unlikely to operate in the same way time pressure does. Given freedom to select information, experts should be able to select useful information items (cue identification) and to weight these cues appropriately (Hoch 1988). In fact, experts may acquire information items that they know are more important early in information processing and may weight these items appropriately higher than less important items acquired later, countering the tendency for recency effects.

Novices may not know which types of information are more important. If they acquire information they consider important early in information processing, they may not weight it significantly higher than information acquired later because they are uncertain about the weight to be given to any information item. Because of this uncertainty, novices should be more likely to apply smaller weights to information items acquired at all stages of information acquisition compared with experts (Hypothesis 1b). In addition, as novices progress through information acquisition they learn more about what attributes are desirable. The relative weight that novices give to information they acquire later may therefore be higher than the relative weight that they give to information they acquire earlier. Although novices resist updating priors early in information acquisition, they compensate for this during the later stages, resulting in a greater relative weight to new information later (vs. earlier) in information acquisition. Their weighting of later information is likely to reflect a cumulative weight given to the combination of all information acquired to that point. In a sense, novices begin to resemble experts during the later stages of information acquisition in the relative weight given to new information (vs. prior evaluation). Experts are able to weight information items appropriately at all stages of information acquisition and therefore do not reflect this tendency to resist updating evaluations until the later stages of information acquisition. Therefore, when consumers control the order of information acquisition,

H2c: Recency effects are less likely to occur under conditions of high category knowledge compared with low category knowledge.

AVERAGING MODELS OF EVALUATION FORMATION

For ease of exposition, we first present the basic averaging model relating current evaluation to prior evaluation and new information. We then generalize this model by introducing the hypothesized moderating effects of time pressure, knowledge, stage of information acquisition, and their interactions.

The Basic Averaging Model

Consistent with information integration theory, consumers are hypothesized to rely on prior evaluation and on new information to form their brand evaluations. Prior evaluation was included in attitude models because it can reconcile the averaging process thought to underlie attitude formation (cf. Hogarth and Einhorn 1992) with the common finding that attitudes become more extreme as the number of information items in the set increases (set size effect; Lopes 1982). Similar models such as our basic averaging model below have been proposed in the literature (e.g., Hogarth and Einhorn 1992) but have only been estimated for data collected in a strictly controlled manner where subjects rate combinations of different levels of experimental stimuli (e.g., Anderson 1982; Zalinski and Anderson 1990). We propose to estimate the model without imposing such controls. We draw on Lopes (1982) and specify the following averaging model to describe the dynamics of the evaluation formation process:

$$A_{it} = A_{i(t-1)} + \sum_{j=1}^{J} w_{ij}(s_{ij} - A_{i(t-1)})X_{ijt} + \varepsilon_{it}, \quad \mathbf{(1)}$$

where:

- A_{it} = consumer i's attitude (i.e., evaluation) at time t;
- $A_{i(t-1)}$ = consumer i's prior attitude (i.e., evaluation);
- X_{ijt} = 1 if information item j is accessed by consumer i at time t ($t = 1, \ldots, T_i$, $j = 1, \ldots, J$), 0 otherwise;
- s_{ij} = scale value for information item j for consumer i;
- w_{ij} = relative weight of information item j on current evaluation for consumer i (w_{ij} varies between 0 and 1); and
- ε_{it} = error term identically and independently distributed (iid) N(0, σ^2) independent of $A_{i(t-1)}$.

Equation 1 assumes that consumers update their evaluations by sequential anchoring and adjustment processes in which prior evaluation serves as the anchor and is adjusted by the impact of new information. This formulation is suitable for a step-by-step response mode in which consumers form on-line judgments and judge a brand after exposure to each item of new information. Equation 1 is a generalization of the averaging model (see Lopes 1982, pp. 7–9) to accommodate integration of multiple information items. Note that X_{ijt} takes a value of 1 only for information item j ($j = 1, \ldots, J$) that consumer i integrates at time t. We use this variable to indicate access of an item of information. Such access can be either controlled or uncontrolled by the researcher. In a later section, we describe a maximum likelihood procedure to estimate the relative weights (w_{ij}) and scale values (s_{ij}) from evaluation data collected in a step-by-step fashion.

This model is similar to that proposed by Hogarth and Einhorn (1992, p. 10, Eq. 3) for estimation tasks such as forming impressions of people. They also suggest that weights given to new information depend on individual and situational variables. However, Hogarth and Einhorn did not formally include such factors in their model and did not estimate the model parameters. They tested model predictions using qualitative tests of deductions from the model about implications for overall judgments. For example, Hogarth and Einhorn inferred order effects from overall judgments when order of information presentation was manipulated. In contrast, we examine the case where consumers are able to control when they access each type of information and infer order effects from the weight given to information that consumers choose to access earlier versus later in information acquisition. Our approach therefore has the benefit of examining order effects in a naturally occurring situation without imposing any constraints on the type of information acquired at any point of time. We extend Hogarth and Einhorn's work by (i) formally including hypothesized moderating factors resulting in a new varying-parameter averaging model and (ii) developing a maximum likelihood approach for parameter estimation.

Modeling the Moderating Effects

Next, we extend the averaging model by incorporating the hypothesized moderating effects. Our hypotheses state that new information is given a greater weight when (1) consumers have high processing ability (Hypotheses 1a and 1b) and (2) the information is seen later versus earlier during information processing, especially for subjects under low time pressure and low category knowledge (Hypotheses 2a, 2b, and 2c).

We model these moderating effects by reparameterizing the relative weights as a linear function of time pressure (TP), knowledge (K), stage of information acquisition (SIA), time pressure by stage of information acquisition interaction (TPSIA) and knowledge by stage of information acquisition interaction (KSIA). Based on prior research (Maheswaran and Sternthal 1990), we also expect the manner in which information is presented (as attribute vs. benefit) to interact with knowledge to affect the weight given to the information. In general, benefits are likely to be weighted more than attributes are. Further, experts (novices) are likely to weight attribute (benefit) information more than novices (experts) do. We therefore include type of information (TI; attribute vs. benefit) and knowledge by type of information interaction (KTI) in the model as controls. Formally, we state this relationship as:

$$\begin{aligned} w_{ijt} = {} & b_{j0} + b_{j1}\mathrm{TP}_i + \mathrm{b}_{j2}\mathrm{K}_i + \mathrm{b}_{j3}\mathrm{SIA}_i \\ & + \mathrm{b}_{j4}\mathrm{TPSIA}_i + \mathrm{b}_{j5}\mathrm{KSIA}_i \\ & + \mathrm{b}_{j6}\mathrm{TI}_{ijt} + \mathrm{b}_{j7}\mathrm{KTI}_{ij} + e_{ijt}, \end{aligned} \quad \mathbf{(2)}$$

where b_{j0} is an intercept term specific to information item j. Since b_{j0} is the value of w_{ijt} when the moderating variables are all equal to 0, it cannot be construed as the main effect of information item j. Parameters b_{j1}–b_{j7} capture the effects of the postulated moderating variables on the relative weight of information item *j*. The variable TP_i takes on a value of 0 (1) when subjects are under low (high) time pressure. Variable SIA_i is the proportion of total trials completed at time *t* by consumer *i*. Variable TI_{ijt} takes on a value of 0 (1) if consumer *i* accessed information item *j* in a benefit (attribute) form at time *t*. The term e_{ijt} is an error term iid $N(0, \delta^2)$, $j = 1, \ldots, J$, assumed to be independent of ε_{it}. Note that w_{ijt} varies over time because of SIA_i. We expect $b_{j1} < 0$ (Hypothesis 1a), $b_{j2} > 0$ (Hypothesis 1b), $b_{j3} > 0$ (Hypothesis 2a), $b_{j4} < 0$ (Hypothesis 2b), $b_{j5} < 0$ (Hypothesis 2c), $b_{j6} < 0$ and $b_{j7} > 0$.

Modeling Scale Values

One of the advantages of the averaging model (as compared with other integration models) is that it separates the importance weights given to information from the scale value of that information. Weights measure importance or psychological impact of information whereas scale values measure the location of information on a relevant dimension of judgment (Eagly and Chaiken 1993). The scale values s_{ij} in Equation 1 can be either obtained directly from consumers or estimated by the model. Direct measurement from consumers has the advantage of statistical efficiency because of the reduced number of parameters to be estimated. However, such self-estimation suffers from the problem of obtaining a common unit for different attributes (Anderson and Zalinski 1990). Anderson (1982) has also noted that there are disadvantages to using self-estimates directly in model estimation such as (1) complications resulting from unreliability in self-estimates and (2) difficulties in attributing deviations in results from predictions to the model versus the measurement.

Alternatively, we can treat scale values as model parameters. However, individual-level scale value estimates are infeasible. In this case we can assume either common scale values for all consumers (as in multidimensional scaling) or that these vary as a function of a priori specified covariates.[1] For example, one would expect experts and novices to differ in their scale values. Similarly, the scale value of benefit information is likely to be different from that of attribute information. Furthermore, it is possible that benefit versus attribute information leads to different scale values for experts and novices.

Our model treats scale values as parameters. However, in contrast to importance weights, we do not have a priori hypotheses about the effects of processing ability and type of information on scale values since these effects are likely to be different for different information items. In this article, we examine individual differences in scale values in an exploratory fashion. Specifically, we use nested model tests to determine if scale values are common or vary as a function of processing ability and/or type of information. For ease of exposition we treat the scale values s_{ij} as fixed (i.e., we ignore covariates) below. See Appendix A for the general model formulation.

The Varying-Parameter Averaging Model

Substituting Equation 2 for w_{ijt} $(j = 1, \ldots, J)$ in Equation 1, the full reparameterized dynamic model of evaluation formation is then given by:

$$A_{it} = \mu_{it} + \zeta_{it}, \tag{3}$$

where:

$$\begin{aligned}\mu_{it} = A_{i(t-1)} + \sum_{j=1}^{J} (&b_{j0} + b_{j1}TP_i + b_{j2}K_i \\ &+ b_{j3}SIA_i + b_{j4}TPSIA_i + b_{j5}KSIA_i \\ &+ b_{j6}TI_{ijt} + b_{j7}KTI_{ijt})(s_{ij} - A_{i(t-1)})X_{ijt},\end{aligned} \tag{4}$$

and

$$\zeta_{it} = \sum_{j=1}^{J} (s_{ij} - A_{i(t-1)})X_{ijt}e_{ijt} + \varepsilon_{it}. \tag{5}$$

Given the distributional and independence assumptions made for the error terms ε_{it} and e_{ijt} $(j = 1, \ldots, J)$, it can easily be shown that A_{it} follows a normal distribution with mean μ_{it} and variance given by:

$$\theta_{ijt}^2 = \sum_{j=1}^{J} (s_{ij} - A_{i(t-1)})^2 X_{ijt}\delta^2 + \sigma^2. \tag{6}$$

Equations 3, 4, and 5 represent a varying-parameter averaging model of evaluation where the relative weights are reparameterized as a function of the hypothesized moderating variables and error. This modeling approach offers five benefits. First, the model uncovers scale values and weights from evaluation data, given naturally occurring information acquisition (i.e., information selected by the subject vs. forced by the experimenter). To our knowledge, such analytical procedures have not been applied on data collected using step-by-step measurement. Empirical estimates of weights in averaging models based on complete factorial designs suffer from uniqueness problems. Although weights and scale values can be estimated separately (Anderson and Zalinski 1990), joint estimation of both parameters requires use of the method of subdesigns (Anderson 1982; Zalinski and Anderson 1990) or varying stimulus factors as well as their levels (Norman 1976). Our approach does not necessitate the use of specific designs and provides unique solutions for the scale and weight parameters. In Appendix A we prove the uniqueness of the weight and scale value parameters. In Appendix B we demonstrate that the scale parameters (s_{ij}) are interval scaled whereas the weight parameters (w_{ijt}) are ratio scaled. Moreover, the scale values can be compared

[1]We thank the associate editor for drawing our attention to this point.

across information items. Note that both proofs consider the general case where weights and scale values are reparameterized as functions of moderating variables.

Second, the model captures individual differences in relative weights given to new information under different time pressure, knowledge, and stage of information acquisition conditions. Third, incorporating stage of information acquisition in the model allows us to test for order effects when order is endogenous (i.e., under control of the decision maker). Previous research on order effects in information integration has studied order effects based on information order imposed by the experimenter. Our approach allows order effects to manifest based on information selection as well as information weight; further, it allows us to look at these order effects under different processing ability conditions. Fourth, the model allows for heteroskedastic error terms since θ^2_{ijt} varies over consumers, information items, and time. Finally, the approach is parsimonious, as it allows pooling data across consumers while retaining individual differences in responses. This parsimony will result in gains in efficiency of the parameter estimates. As such, it is useful for testing moderating effects in the context of averaging models.

Generally, this varying-parameter approach can be used to analyze data from experiments using process-tracing methodologies where the dependent variable is continually measured after accessing each information item (as in Jacoby et al. 1994) and where the process can be represented by an averaging model. Typically, subjects are free to acquire any amount of information in any order in such experiments. Thus, data analysis procedures that take into account issues such as different amounts of total information acquired across subjects, different types of information at each time, and repeated measurement of the dependent variable after accessing each item of information are required. The proposed modeling approach, where the weight given to each item of information is reparameterized as a function of moderating variables, is flexible and easy to use. For example, order effects can be estimated without experimental manipulation of order of information (e.g., strong-weak vs. weak-strong) as is typically done to infer order effects (e.g., Hogarth and Einhorn 1992).

Note from Equations 3, 4, and 5 that the varying-parameter averaging model of evaluation formation simplifies to the basic averaging model in Equation 1 under two conditions: (1) if there is no error in the coefficients w_{ijt} ($j = 1, \ldots, J$) and (2) if time pressure (TP), knowledge (K), stage of information acquisition (SIA), the interaction of SIA with TP and K, and type of information (TI) and its interaction with knowledge (KTI) exert no moderating role on the effects of new information on current evaluation (i.e., when the parameters b_{j1}–b_{j7}, and δ^2 are all equal to zero). This shows that the basic averaging model in Equation 1 is nested within the varying-parameter averaging model. Therefore, a log likelihood ratio test can be used for model selection. A significant improvement in fit suggests that the hypothesized moderating factors play a significant role in evaluation formation.

Estimation Procedure

By assumption, A_{it} follows a univariate normal distribution with mean μ_{it} and variance θ^2_{ijt}. Then, assuming independence over trials, the likelihood function for a randomly drawn consumer observed over T_i trials is

$$L_i = \prod_{t=1}^{T_i} \frac{1}{\theta_{ijt}} \phi\left(\frac{A_{it} - \mu_{it}}{\theta_{ijt}}\right),$$

where $\phi(.)$ is the univariate normal density function. The likelihood function for a sample of n randomly drawn consumers is then

$$L = \prod_{i=1}^{n} L_{i,}$$

where L is a function of b_{j0}–b_{j7}, $j = 1, \ldots, J$, s_{i1}–s_{iJ}, σ and δ. The problem is to maximize L or ln L with respect to the parameters, given the sample data, while taking into account the constraints $\sigma > 0$, $\delta > 0$, and $0 < w_{ijt} < 1$. To facilitate estimation, we should impose the constraint $0 < w_{ijt} < 1$ only when the unconstrained maximization of ln L fails to produce proper parameter estimates. One approach that can be used to bound the relative weights between 0 and 1 is to rewrite Equation 2 as

$$w_{ijt} = \frac{\exp(\overline{w}_{ijt})}{1 + \exp(\overline{w}_{ijt})} + e_{ijt},$$

where

$$\overline{w}_{ijt} = b_{j0} + b_{j1}TP_i + b_{j2}K_i + b_{j3}SIA_i + b_{j4}TPSIA_i + b_{j5}KSIA_i + b_{j6}TI_{ijt} + b_{j7}KTI_{ij}.$$

Maximum likelihood estimators have desirable properties of being asymptotically consistent, efficient, and normal (see Ben-Akiva and Lerman 1985, p. 15). We used Proc NLP in SAS for this maximization problem. The SAS program code is available from the authors. In the next section, we describe the experiment conducted to test the hypotheses by estimating the models discussed above.

METHOD

Computer Simulation

This experiment tests hypotheses regarding on-line attitude formation using a step-by-step measurement. We did this using computer-based process tracing where the subject is shown the types of information available on the computer screen. The subject then accesses one information item at a time, accessing only those items that s/he desires in any order, and continually evaluates the product.

Subjects were provided with access to information for one brand of personal computer on 23 attributes and the corresponding benefits. Some features on which information was provided include availability, coprocessor, floppy drives, memory, operating system, and microprocessor. The experiment was run in the early 1990s and the information may therefore seem dated. As an example, attribute information on microprocessor said ''Intel 80486 chip'' and benefit information said ''latest technology.'' See Table 2 for a list of all the features.

Access of an item of information is termed a trial. To assess the impact of information at each trial, we used an extension of Behavioral Process Technology described by Jacoby et al. (1985, p. 111; 1987; 1994). This extension requires subjects to respond to the dependent measure after each trial, that is, after they access each item of information. Specifically, subjects are asked to judge the described brand after accessing each item of information that they select about the brand (see also Hauser, Urban, and Weinberg 1993).

Procedure

Ninety-one students at a large northeastern university participated in this experiment for partial course credit. Subjects were randomly assigned to the no time pressure or high time pressure conditions. Each subject was seated before an IBM personal computer in a separate cubicle. The first screen informed subjects that their college bookstore needed their help in deciding whether to stock a new personal computer. Their goal was therefore to evaluate the personal computer (an impression formation goal). Subjects first responded to a questionnaire on their use of personal computers including a question asking them to rate their familiarity with personal computers on a seven-point scale anchored at ''not at all familiar'' and ''very familiar.'' Next, subjects proceeded to the computer-based tasks. To familiarize them with the software and attitude scales, subjects were first run through a practice task that required them to evaluate a new diet soft drink based on information about 10 attributes and benefits. Subjects then proceeded to evaluate the new personal computer brand.

Subjects assigned to the no time pressure condition were told at the start of the experiment that they had unlimited time to process the information presented whereas high time pressure subjects were told that they would have only five minutes to select and read information. This instruction was expected to make subjects feel time pressure. In addition, it imposed a time constraint on the task. Instructions regarding the use of the software were presented again. Next, an information matrix was displayed on the computer screen. Containing 46 cells representing different information items, the matrix had 23 rows and two columns labeled ''attribute'' and ''benefit.'' Organized alphabetically, the row information identified features of a personal computer, starting with ''availability'' and ending with ''warranty and service.'' Only the labels of the 23 rows (names of features) and two columns (labeled ''attribute'' and ''benefit'') were visible; subjects had to move the cursor to a specific cell (e.g., attribute information on the price feature) in the matrix to request that information. Subjects could access either attribute or benefit information about a certain feature in each trial; in two trials they could access both attribute and benefit information on the same feature, if desired. They could also access information about as many features as they desired in any order. No-time-pressure subjects could stop acquiring information at any time; high-time-pressure subjects were forced to stop after five minutes. After accessing and reviewing each piece of information, subjects were asked to respond to a nine-point evaluative scale anchored by ''not at all favorable'' (1) and ''very favorable'' (9).

After the computer phase of the experiment, subjects were given a second questionnaire, with no time limits imposed for completion. The time pressure manipulation was checked via the question ''How did you feel about the time that you had to see the information?'' and the seven-point response scale was anchored at ''did not have enough time'' (1) and ''had enough time'' (7). To ensure that the information made available was fairly exhaustive, subjects were also asked to identify any other information they would have liked to consider in evaluating the personal computer. Objective knowledge of personal computers was then measured using 10 true/false/don't know questions. These questions related to knowledge of the product category and could not be answered based on brand information acquired in the study. Finally, subjects responded to some demographic questions. Subjects were then debriefed and thanked for their participation. In addition, the computer stored information on the name of the attribute/benefit accessed on each trial, the total number of trials, and the sequence in which items were accessed.

RESULTS

Overview

Manipulation Checks. The time pressure manipulation worked as intended. Subjects in the no-time-pressure condition felt they had sufficient time ($\bar{X} = 5.59$, $n = 44$) whereas subjects in the high-time-pressure condition felt they had less time ($\bar{X} = 3.53$, $n = 47$; $t(89) = 5.33$, $p < .01$, $\eta^2 = 0.24$). The manipulation check question measures whether subjects in the high-time-pressure condition were aware that they had insufficient time to perform the evaluation task but may not reflect whether they actually felt time pressure during the task or whether the time given to them was sufficient to perform the task. Additional evidence for the success of the manipulation comes from the amount of processing in the two conditions. No-time-pressure subjects accessed more information items ($\bar{X}$ = 12.41) than did high-time-pressure subjects ($\bar{X}$ = 9.51; $t(89) = 2.19$, $p < .05$, $\eta^2 = 0.05$).

Information Provided. The information made available in the matrix can be assumed to have been reasonably sufficient for reaching a decision, since the mean amount of additional information desired by subjects was only 1.60. Debriefing also revealed that virtually all subjects felt the most important information was available to them. The order in which information items were presented was correlated with the order of information access ($r = 0.38$, $p < .01$), but the presentation order accounted for only 14 percent of the variance in order of access. Thus, subjects acquired information based on order of presentation but also used other criteria in selecting which information to acquire on each trial.

Expertise. Each correct response on the knowledge quiz scored one point. A ''don't know'' response was included in the true-false questionnaire on personal computer knowledge to improve scale reliability by reducing pressures for guessing (see Schmittlein and Morrison 1983). The mean score on the knowledge quiz was 5.64, and the scores ranged from 2 to 8. Experts devoted more of their information acquisition to attributes than did novices, as evidenced by the significant positive correlation between the continuous knowledge score and the proportion of trials on which attributes were accessed ($r = 0.31$, $p < .001$). This finding that experts seek out attribute information more than novices do is consistent with prior research, which has suggested that experts (novices) find attribute (benefit) information more informative than novices (experts) do (Conover 1982). This preference appears to manifest itself in information selection as well as in information processing when attribute and benefit information are provided to subjects as was done by Maheswaran and Sternthal (1990).

Subjects with a knowledge score at or above the median of 6 were classified as experts ($n = 48$) and those with a score below 6 were classified as novices ($n = 43$) for a preliminary analysis. On average, experts accessed 6.81 attributes compared with novices, who accessed 6.16 attributes ($p > .4$). The mean number of benefits accessed by experts was 3.31 compared with 5.28 for novices ($t(89) = 1.97$, $p = .05$). Each subject's knowledge score was retained and used for the model estimation presented in the next section.

Below, we discuss the varying-parameter averaging model estimation. Note that traditional ANOVA approaches (e.g., repeated-measures designs) cannot be used to test our hypotheses for several reasons. First, as the amount of information was not researcher imposed, different subjects accessed different amounts of information. Second, the order in which information was acquired was not controlled. As in the real world, subjects were free to access any information they wanted, in any order, and to stop accessing information at any time. Third, the relative weighting of prior evaluation and new information as well as the magnitude of the impact of moderating variables cannot be assessed using ANOVA.

Model Estimation

Operationalization. Variables in the varying-parameter averaging model in Equation 3 were operationalized as follows. Prior evaluation (A_{t-1}) was operationalized as the evaluation prior to acquisition of the new item of information. Type of information (TI) was coded as a dummy variable, with benefit information equal to 0 and attribute information equal to 1. Time pressure (TP) was coded as 0 = no time pressure and 1 = high time pressure. Each subject's score on product category knowledge (K) was divided by 10 to vary from 0 to 1. Stage of information acquisition (SIA) was operationalized as the trial number divided by the total number of trials for that subject. It therefore represents the proportion of information acquisition completed at each stage for each subject and is used to test hypotheses regarding recency effects. The SIA variable captures the differential weighting of the same item of information seen early versus late (in a continuous sense) in information processing.

Model Specification. We constrained the moderating effects of the weight of new information to be invariant across all 23 information items in Equation 3 so that $b_{j1} = b_1, \ldots,$ and $b_{j7} = b_7$. However, we set the intercepts b_{j0} ($j = 1, \ldots, J$) free. Thus, differences in information item effects are only captured by the intercept terms, and we assume that the moderating variables affect all 23 items in the same way. This was done for two reasons. First, we do not have a priori expectations regarding the moderating impact of knowledge and time pressure on each individual information item. Our hypotheses only relate to the evaluation formation process as a function of new information in general. Second, we wanted to make the model parsimonious by limiting the number of parameters to be estimated. If we had not constrained the model in this way, we would need to estimate 154 additional parameters (22×7) for the moderating effects of new information.

To capture variability in scale values, we allowed these parameters to depend on knowledge, time pressure, and type of information. In contrast to new information weights, we allowed the moderating effects of scale values to vary freely across the 23 information items. This is because, unlike weights, we do not have a priori hypotheses regarding the directionality of the moderating effects. Second, we expect that the moderating effects are likely to be different for different information items. For example, scale values for benefits may be higher than those for attributes for technical features but not for other features.

Model Estimation Results

We estimated nine different models. We first estimated the basic averaging model, where both information

TABLE 1

SUMMARY STATISTICS FOR MODEL SELECTION

Model	Degrees of freedom	$-\ln L$	Likelihood-ratio test
Basic model:			
Common scale values	75	1,127.9	179.8
Varying-parameter model:			
Common scale values	68	1,104.9	133.8
Scale values vary by:			
Knowledge	45	1,096.5	117.0
Type of information	46	1,063.7	51.4[a]
Time pressure	45	1,095.4	114.8
Knowledge and type of information	23	1,052.0	28.0[a]
Time pressure and knowledge	22	1,090.4	104.8
Time pressure and type of information	23	1,050.9	25.8[a]
Time pressure, knowledge and type of information	. . .	1,038.0	. . .

NOTE.—One information item (manufacturer) was provided as one type of information only. Nested models sharing the same superscripts are not significantly different from the saturated model, which includes time pressure, knowledge, and type of information.

weights and scale values are invariant across subjects. Next, we estimated the varying-parameter averaging model (Eq. 3) with common scale values (i.e., $s_{ij} = s_j$ for all i). We then estimated seven varying-parameter averaging models with scale values varying as a function of (i) knowledge only, (ii) type of information only, (iii) time pressure only, (iv) knowledge and type of information, (v) knowledge and time pressure, (vi) type of information and time pressure, and (vii) knowledge, type of information, and time pressure. Table 1 provides the summary statistics for model selection.

Because the nine models are nested, we use the likelihood ratio test for model selection. This test points to the varying-parameter averaging model with scale values varying as a function of type of information only. The fit of the selected model is significantly better than those of the varying-parameter averaging model with common scale values (χ^2 (22) = 82.4, $p < .001$) and the basic averaging model (χ^2 (29) = 128.4, $p < .001$). It is also not significantly different from the saturated model, where scale values depend on type of information, knowledge, and time pressure (χ^2 (46) = 51.4, $p > .25$). These results show that processing ability, type of information, stage of information, and their interactions are all significant moderators of information weights. They also show that scale values depend only on type of information.

To test the extent to which benefit versus attribute information leads to different scale values for experts and novices, we also estimated a varying-parameter averaging model, where scale values vary as a function of knowledge, type of information, and their interaction. The likelihood ratio test shows that the fit of this model is not significantly different from that of the selected model (χ^2 (45) = 50.9, $p > .25$). Thus, it appears that benefit versus attribute information did not lead to different scale values for experts and novices.

Table 2 presents the results of the selected varying-parameter averaging model with scale values differing by attribute versus benefit.

Scale Values

Estimation of the varying-parameter averaging model provides scale values for each of the 23 information items presented in attribute or benefit form. These scale values refer to the ''favorability'' of the information provided to subjects, regardless of its importance. These results cannot be generalized and relate only to the specific information provided in this experiment. First, note that scale values are generally high, reflecting the positive information provided. Second, scale values for attributes were significantly different (p's $< .05$) from those for benefits for three information items: benefit information has lower scale value for memory expansion and higher scale values for processor speed and price.

The memory expansion attribute information stated, ''Can be expanded to 10 megabytes''; this was considered to be more favorable than the benefit information, which stated, ''While the information on some PC's can be expanded further you rarely need more than 10 megabytes.'' A reason for these scale values may be that the benefit information provided some negative information because it stated that other models allow further expansion.

Benefit information was valued more than attribute information for processor speed and price. Attribute information on processor speed stated, ''25 megahertz,'' and benefit information stated, ''The fastest possible speed.'' Price attribute information stated, ''Discounted to \$2,500,'' and benefit information stated, ''\$1,000 lower than the discounted prices for a comparable IBM personal computer.'' The benefit information in these cases is

TABLE 2

VARYING-PARAMETER AVERAGING MODEL RESULTS

	Scale values (s_j)		Average weights (w_j)		
	Attribute	Benefit	Mean	Minimum	Maximum
Information items:					
Availability	9.00	2.12	.015	.010	.067
Compatibility	7.22	6.94	.160	.024	.335
Coprocessor	6.03	5.45	.516	.333	.664
Country of manufacture	4.97	4.52	.124	.044	.224
Floppy drives	6.46	7.57	.203	.033	.345
Graphics	8.38	8.61	.176	.033	.315
Input devices	6.75	7.24	.233	.118	.368
Internal hard disk storage	8.12	6.36	.196	.039	.309
Keyboard	4.69	5.61	.107	.007	.190
Manufacturer	. . .	5.19	.401	.313	.488
Memory (RAM)	6.25	6.81	.171	.062	.286
Memory expansion	8.97[a]	7.17[b]	.192	.070	.308
Microprocessor	7.57	8.31	.428	.350	.518
Modem	7.87	8.97	.189	.033	.291
Networking	6.41	8.89	.266	.153	.363
Number and type of interfaces	6.79	2.74	.218	.109	.331
Operating system	8.90	8.89	.167	.042	.249
Processor speed	5.40[a]	9.00[b]	.183	.012	.280
Price	5.66[a]	8.72[b]	.285	.056	.392
Size	7.19	8.74	.165	.051	.239
Software	7.22	8.65	.174	.004	.247
Sound	6.82	7.88	.459	.419	.503
Warranty	7.71	8.92	.170	.017	.262

	Parameter	Value
Moderating effects:		
Time pressure (TP)	b_1	−.10*
Knowledge (K)	b_2	.47*
Type of information (TI)	b_3	−.14
Stage of information acquisition (SIA)	b_4	.40*
TP × SIA	b_5	.11
K × SIA	b_6	−.58*
K × TI	b_7	.26
Error term standard deviations:		
Error in relative weights	δ	.10
Error in equation	σ	.75

NOTE.—Manufacturer information was provided in one form only. Attribute and benefit scale values with different superscripts are significantly different at $p < .05$.
*Significant at $p < .05$.

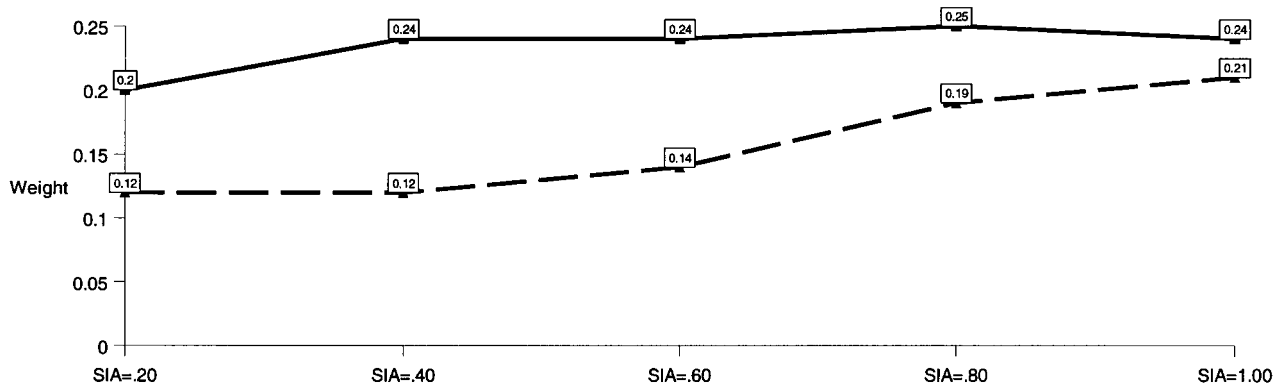
clearly more favorable than the corresponding attribute information, lending the scale values some face validity.

The lowest scale values were observed for benefit information on availability (2.12) and number and type of interfaces (2.74). Availability benefit information stated, ''The dealership agreement with Microsoft makes information on and service for this computer widely available.'' This information may have low value because Microsoft was not a household name at the time that this experiment was conducted. Further, the scale values represent average values across subjects, and other information that subjects had seen may have been perceived as intrinsically better than this description of availability. Benefit information on number and type of interfaces stated, ''Enables you to connect to printers and modem'' and may have had low scale value because it was not comprehended by subjects.

Scale values for attribute information on country of manufacture (''Chip made in the USA. Assembled in the Far East'') and keyboard (''IBM extended keyboard with 101 keys and 3 lighted indicators'') were the lowest. Information on country of manufacture may be perceived negatively because it stated that assembly was in the Far East. Finally, high scale values were observed for information on operating system, graphics, and modem. This information was interpreted by subjects to be more posi-

FIGURE 1

INFORMATION WEIGHTS OF EXPERTS VERSUS NOVICES OVER STAGE OF INFORMATION ACQUISITION (SIA)



NOTE.—The solid line indicates experts; the dashed line indicates novices.

tive than information provided on other features of the personal computer.

We had collected pretest data on the positivity of some of the attribute information presented to subjects. Support for the validity of the scale values comes from the significant correlation between the pretest data and the scale values ($r = .47$).

Average Weights

Weights represent the importance given to each information item as reflected by the extent to which evaluations are updated after seeing information items varying in ''goodness.'' Estimating the model in Equation 3 provided values for each of the b_j's. These were plugged into Equation 2 along with the values for each subject's knowledge score, time pressure condition, stage of information acquisition, and type of information to compute the predicted weight ($\hat{w}_{ijt}$) for each subject to the information items that s/he accessed at trial *t*. These weights were then averaged across subjects and trials. The top portion of Table 2 reports these average weights and their corresponding range. The minimum and maximum weights reveal that there is a remarkable amount of heterogeneity across subjects in terms of weights given to information items. This heterogeneity is partially explained by the moderating factors discussed in the next section. Note that the relative weights all fall in the [0, 1] range as expected without imposing any constraints.

Relative weight given to evaluation prior to accessing each information item can be computed as $(1 - w_{ijt})$ based on the averaging model assumed to underlie evaluation formation. Coprocessor is given the highest weight of 0.52. Coprocessor attribute information stated, ''Math coprocessor Intel 89487. Available for a small fee,'' and benefit information stated, ''Allows you to perform advanced mathematical computations.'' Microprocessor information was also weighted heavily (0.43); attribute information stated, ''Intel 80486 chip,'' and benefit information stated, ''Latest technology.''

Lowest weights were given to availability (0.015) and keyboard (0.107). Benefit information for availability and attribute information for keyboard has been provided in the section on scale values. Availability attribute information stated, ''The company has entered into dealership agreements with Microsoft.'' Keyboard benefit information stated, ''Typewriter format keys and an additional number pad to easily enter data.''

Testing the Hypotheses

Ability to process information as operationalized by time pressure and knowledge had the hypothesized effects on the relative weights given to new information. As expected (Hypothesis 1a), new information affects evaluations of no time pressure subjects more than those of high time pressure subjects ($b_1 = -0.10$, $p < .05$). Hypothesis 1b, which states that new information affects evaluations more under high category knowledge than low category knowledge, is also supported ($b_2 = 0.47$, $p < .05$).

Hypotheses 2a, 2b, and 2c relate to order effects in evaluation formation. Hypothesis 2a suggests that recency effects will be observed in this continuous updating situation. This hypothesis is supported ($b_4 = 0.40$, $p < .05$). As the proportion of information acquisition that is completed increases, the weight given to new information increases. Inconsistent with Hypothesis 2b, time pressure does not appear to moderate this effect ($b_5 = 0.11$, $p = .12$). Hypothesis 2c, which states that recency effects are less likely under conditions of high category knowledge compared with low category knowledge, is supported ($b_6 = -0.58$, $p < .05$). Figure 1 illustrates the simple effects of knowledge at different stages of information acquisition.

Two related processes can account for this finding. First, high knowledge subjects may access more important information items earlier in information processing than novices do. Correlations between the order in which information items were presented and information acquisition order were similar for high ($r = 0.39$) and low knowledge subjects ($r = 0.36$, $z = 0.56$, $p > .5$), as defined by a median split of knowledge scores. Thus, there is no evidence that experts were more likely to ignore information presentation order, and access information that they rated important early, compared with novices. However, these correlations do not argue against this reasoning.

Some support for this first process comes from the proportion of the first five trials that experts versus novices (as defined by a median split) devoted to specific properties. For example, experts (novices) devoted 20 percent (12 percent) of their first five trials to compatibility information ($z = 2.17$, $p < .05$). Experts were also more likely than novices to access information on speed (6 percent vs. 1 percent, $z = 2.40$, $p < .05$) during the first five trials. Thus, experts differ from novices in the order in which they acquire information. They appear more likely than novices to select important information during the early stages of information acquisition.

The second reason for the support for Hypothesis 2c arises from cue weighting in the absence of cue selection. High knowledge subjects may simply weight information items more appropriately regardless of when they are acquired. However, low knowledge subjects may be uncertain about the weight to give information items and may weight later (vs. earlier) items more based on cumulative information. Cue weighting would therefore result in recency effects for low knowledge subjects but would result in reduction in recency effects for high knowledge subjects. Supporting this reasoning, Figure 1 shows that experts weight items acquired later (after the first 20 percent) consistently over different stages of information acquisition whereas novices weight information acquired later more than information acquired earlier. Experts seem to acquire only that information they consider important.

Finally, benefit information has a greater impact on attitudes than attribute information does ($b_6 = -0.19$, $p < .10$). However, the weight given to attributes versus benefits does not appear to depend on knowledge ($b_7 = 0.26$, $p = .11$). As discussed earlier, presenting information in attribute-versus-benefit form affected the scale values for some features significantly.

DISCUSSION

Overview of Results

In general, evaluation formation is viewed as a function of information input. New information plays a smaller role in evaluation formation when ability to process information is low, as occurs when (*a*) consumers are under high-time-pressure conditions or (*b*) consumers have low levels of knowledge about the product category. Equivalently, new information is more likely to be integrated into evaluations when ability to process information is high, as occurs when (*a*) consumers are under no time pressure or (*b*) consumers have high levels of knowledge about the product category.

Our model also allows an examination of order effects. Consistent with our hypothesis, when evaluations are formed on-line, there is a tendency for recency effects: information acquired later is given greater weight than that acquired earlier. The tendency to weight later information items more highly than earlier items decreases with an increase in category knowledge. An explanation for this finding is that knowledgeable subjects chose only the more important information items and weighted them appropriately. Recency effects are not moderated by time pressure.

Contributions

Theoretical. From a theoretical standpoint, we extend the attitude literature in two ways. First, we integrate process models of persuasion with algebraic models by conceptualizing the moderating effects of ability to process information on evaluation formation as affecting the weight given to new information. Second, we examine order effects on weights when order is endogenous, whereas all the prior order effects literature considers only the case in which the order is externally imposed. Further research is needed to determine the relative importance of cue selection versus cue weighting in the reversal of the recency effect for high knowledge subjects.

This research represents a start in building attitude formation models based on hypotheses derived from process theories of persuasion. Researchers studying attitudes have called for such joining of information integration theory to process theories of persuasion. As Eagly and Chaiken (1993, p. 251) state, ''The advantages of such linkages are twofold: (a) from the perspective of information integration theory, additional ability is gained to identify the determinants of weights; and (b) from the perspective of the process theories, a mathematical description is gained of the impact of process-relevant cues, including the simultaneous impact of several such cues.''

This research also suggests that evaluations formed under low ability conditions can be relatively resistant to change. Prior research has identified various motivational and cognitive reasons for resistance to attitude change. Motivational reasons include threats to the ego or to the stability of important attitudes. The cognitive perspective suggests that attitudes linked to many other cognitions resist change because of the possibility of destabilization of large cognitive structures or because strong attitudes help people ward off attacks on attitudes. Our research suggests that attitudes may be resistant to change under conditions of low ability because people are uncertain about how new information should be weighted. Paradoxically, attitudes formed under low ability may be relatively weak but may still be resistant to change when impressions are being formed rather than tested (Higgins and Bargh 1987). This speculation, as well as the hypothesized uncertainty process, is in need of empirical verification.

In this research, information integration theory was applied at a relatively molecular level, with each unit being a single item of information rather than an entire communication, as is commonly modeled. This level of analysis was possible because we used a continuous tracing methodology (see Jacoby et al. 1994) to study attitude formation. This research represents the first attempt to model attitudes using this procedure and provides new insights into the attitude formation process.

Methodological. We make three methodological contributions. First, we develop a methodology to derive scale values and weights of information using step-by-step evaluation data. Using prior formulations of the averaging model believed to underlie attitude formation (Lopes 1982), we developed a procedure to estimate the various parameters. Previous research has used relatively sterile environments and controlled procedures to capture information on weights (Anderson 1982). Experiments were constructed using specific types of partial designs in order to derive scale values and weights. We present a maximum likelihood procedure to estimate weights and scale values given naturally occurring information acquisition. To our knowledge, averaging models have not been previously estimated using continuous attitudinal data.

Second, the model and estimation procedure also allow us to capture the moderating effects of other variables on the relative weight given to new information. The varying-parameter averaging model used in this research captures the complexity underlying attitude formation and can be used to study such dynamic processes under different boundary conditions. This model is capable of taking various factors (e.g., prior evaluation, type of information, and stage of information acquisition) into account that could not be considered using simple data analytic techniques, such as ANOVA and regression, or using the basic averaging model used in prior research. The model can also estimate scale values for different segments in the population and for different types of information.

Finally, our model and estimation procedure can also be used to detect order effects and, as discussed below, has several advantages compared with traditional ANOVA techniques used for this purpose (Hogarth and Einhorn 1992; Kruglanski and Freund 1983). Recent researchers have criticized the use of change scores such as those traditionally used in studying order effects for their low reliability (Peter, Churchill, and Brown 1993). In contrast, our modeling procedure captures order effects without directly comparing the change in attitudes when information is presented in a strong-weak versus a weak-strong order (e.g., Hogarth and Einhorn 1992). Using continuous data and without controlling the order in which information is accessed, we were able to uncover recency effects in attitude formation.

Our procedure imposes no need to manipulate strength of information items. Rather, it is possible to uncover order effects by considering the weight given to new information as the proportion of information accessed changes for each subject. Estimating order effects when order of information acquisition is endogenous (i.e., controlled by the subject) captures the effects of information selection by the subject as well as information weighting. The first effect would be omitted in traditional research on order effects where order is exogenous. For the sake of simplicity, we held the moderating effects of proportion of information accessing completed, on the weight given to new information, to be constant across different information items. The model could be extended to capture differences in the moderating effects across information items.

Another advantage of our approach to detecting order effects compared with the traditional analyses is that, rather than using initial and final evaluations only, we use evaluations as they are in the process of being formed. Finally, we can utilize complete information from continuous variables such as knowledge without resorting to dichotomizing the scale.

This research increases our understanding of the attitude formation process. As Eagly and Chaiken (1993, p. 255) state, ‘‘Any general theory of persuasion must in the long run incorporate both elements of combinatorial models and elements of process theories.’’ Although this research represents a start in this direction, additional research is needed to combine these different paradigms in the study of attitudes.

APPENDIX A

The Identification of the Varying-Parameter Averaging Model

Consider the varying-parameter averaging model

$$\begin{aligned} A_{it} - A_{i,t-1} &= \sum_{j=1}^{J} w_{ijt}(s_{ij} - A_{i,t-1})X_{ijt} + \varepsilon_{it} \\ &= \sum_{j=1}^{J} w_{ijt}s_{ij}X_{ijt} \\ &\quad - \sum_{j=1}^{J} w_{ijt}A_{i,t-1}X_{ijt} + \varepsilon_{it}. \end{aligned} \tag{A1}$$

Suppose w_{ijt} and s_{ij} are further reparameterized as functions of the moderating variables z_{ilt}, $l = 1, \ldots, L$ and D_{im}, $m = 1, \ldots, M$, respectively, where the Z's and D's do not need to be different. Thus,

$$w_{ijt} = w_{j0} + \sum_{l=1}^{L} \alpha_{jl}Z_{ilt} + e_{ijt}, \tag{A2}$$

and

$$s_{ij} = s_{j0} + \sum_{m=1}^{M} \gamma_{jm} D_{im} + u_{ij}, \tag{A3}$$

where the α's and γ's are parameters and e and u are error terms.

For simplicity, assume $L = 1$, $M = 1$, and no error in w_{ijt} and s_{ij}. Then the reduced-form varying-parameter averaging model is

$$\begin{aligned} A_{it} - A_{i,t-1} &= \sum_{j=1}^{J} (w_{j0} + \alpha_{j1} Z_{i1t})(s_{j0} + \gamma_{j1} D_{i1}) X_{ijt} \\ &\quad - (w_{j0} + \alpha_{j1} Z_{i1t}) A_{i,t-1} X_{ijt} + \varepsilon_{it} \\ &= \sum_{j=1}^{J} w_{j0} s_{j0} X_{ijt} + w_{j0} \gamma_{j1} D_{i1} X_{ijt} \\ &\quad + \alpha_{j1} s_{j0} Z_{i1t} X_{ijt} + \alpha_{j1} \gamma_{j1} D_{i1} Z_{i1t} X_{ijt} \\ &\quad - w_{j0} A_{i,t-1} X_{ijt} - \alpha_{j1} Z_{i1t} A_{i,t-1} X_{ijt} + \varepsilon_{it} \\ &= \sum_{j=1}^{J} \beta_{j1} X_{ijt} + \beta_{j2} D_{i1} X_{ijt} + \beta_{j3} Z_{i1t} X_{ijt} \\ &\quad + \beta_{j4} D_{i1} Z_{i1t} X_{ijt} - \beta_{j5} A_{i,t-1} X_{ijt} \\ &\quad - \beta_{j6} Z_{i1t} A_{i,t-1} X_{ijt} + \varepsilon_{it}, \end{aligned} \tag{A4}$$

where

$$\begin{aligned} \beta_{j1} &= w_{j0} s_{j0}, \\ \beta_{j2} &= w_{j0} \gamma_{j1}, \\ \beta_{j3} &= \alpha_{j1} s_{j0}, \\ \beta_{j4} &= \alpha_{j1} \gamma_{j1}, \\ \beta_{j5} &= w_{j0}, \\ \beta_{j6} &= \alpha_{j1}. \end{aligned}$$

Since A_{it}, X_{ijt}, Z_{ijt}, and D_{il} are all observed, then the β_{ji} ($i = 1 \ldots 6$; $j = 1 \ldots J$) are identified using standard regression theory. Hence

$$\begin{aligned} w_{j0} &= \beta_{j5}, \\ \alpha_{j1} &= \beta_{j6}, \\ \gamma_{j0} &= \frac{\beta_{j1}}{\alpha_{j0}}, \\ \gamma_{j1} &= \frac{\beta_{j2}}{\alpha_{j0}}. \end{aligned}$$

This proof of identifiability generalizes to any value of L and M.

If w_{ijt} and s_{ij} include the error terms e_{ijt} and u_{ij}, respectively, then the overall error in Equation A4 is heteroskedastic. It is straightforward to show that this model is identified. (The only difference from the previous case is that the regression model is now heteroskedastic.)

APPENDIX B

The Measurement Properties of the Weight and Scale Parameters

Suppose subject i accesses information item j at trial t (i.e., $X_{ijt} = 1$), then the error-free averaging model reduces to

$$A_{it} - A_{i,t-1} = w_{ijt} s_{ij} - w_{ijt} A_{i,t-1}. \tag{B1}$$

Proposition. Suppose that A_{it} is interval scaled. Then the weight parameter w is ratio scaled, whereas the scale parameter s is interval scaled.

Proof. By assumption, the variable A_{it} is interval scaled. Thus there exists scaling factors b and c such that $A^*_{it} = \mathrm{b}A_{it} + c$, where $\mathrm{b} > 0$ (the affine transformations are the only allowable transformations for rescaling interval scaled variables). Let w^*_{ijt} and s^*_{ij} be the corresponding rescaled model parameters such that:

$$A^*_{it} - A^*_{i,t-1} = w^*_{ijt} s^*_{ij} - w^*_{ijt} A^*_{i,t-1}. \tag{B2}$$

Then we seek to show (1) $w^*_{ijt} = w_{ijt}$ (i.e., the weight parameter w is ratio scaled), and (2) $s^*_{ij} = \mathrm{b}s_{ij} + c$, where $\mathrm{b} > 0$ (i.e., the scale parameter s is interval scaled).

Multiplying Equation B1 by the scaling factor b we get:

$$\mathrm{b}(A_{it} - A_{i,t-1}) = \mathrm{b}w_{ijt} s_{ij} - \mathrm{b}w_{ijt} A_{i,t-1}. \tag{B3}$$

Adding and subtracting $c \times w_{ijt}$ to the right-hand side of Equation B3 and noting that $A^*_{it} - A^*_{i,t-1} = \mathrm{b}(A_{it} - A_{i,t-1}),$ we obtain:

$$A^*_{it} - A^*_{i,t-1} = w_{ijt}(\mathrm{b}s_{ij} + c) - w_{ijt} A^*_{i,t-1}, \tag{B4}$$

or equivalently,

$$w^*_{ijt} s^*_{ij} - w^*_{ijt} A^*_{i,t-1} = w_{ijt}(\mathrm{b}s_{ij} + c) - w_{ijt} A^*_{i,t-1}. \tag{B5}$$

Equation B5 implies that the following two equalities must hold:

$$w^*_{ijt} s^*_{ij} = w_{ijt}(\mathrm{b}s_{ij} + c), \tag{B6}$$

$$w^*_{ijt} = w_{ijt}. \tag{B7}$$

Hence,

$$s^*_{ij} = \mathrm{b}s_{ij} + c, \tag{B8}$$

$$w^*_{ijt} = w_{ijt}, \tag{B9}$$

concluding the proof.

Note that if s_{ij} and w_{ijt} are reparameterized as a function of moderating variables D_{im} and Z_{ilt}, respectively (see Eqq. A2 and A3 in App. A), it is easy to show that (1) w_{j0} ($j = 1, \ldots, J$) are ratio scaled, (2) s_{j0} ($j = 1 \ldots J$) are interval scaled, and (3) all the moderating parameters α_{jl} and γ_{jm} are ratio scaled.

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