BREAKING OPEN THE CONSUMER BEHAVIOR BLACK BOX: SEM AND RETAIL ATMOSPHERIC MANIPULATIONS

Richard Michon and Jean-Charles Chebat

Few marketing researchers employ structural equation modeling (SEM) with experimental data. In fact, as stressed here, SEM has the capacity to measure consumers' response to experimental manipulations as well as affective and cognitive processes leading to these behavioral responses. A structural equations approach has several possible advantages over a traditional multivariate analysis of variance approach including handling latent variables with measurement errors and isolating mediating effects between endogenous variables. The authors provide some specific examples drawn from retail atmospheric experimental data.

Contrary to other linear methods in the social sciences, structural equation modeling (SEM) generates a great deal of passionate reactions. SEM has its champions and detractors, as reported by Baumgartner and Homburg (1996). The former (Anderson and Gerbing 1984; Bagozzi 1984; Bagozzi and Yi 1988; Dillon 1986; Steenkamp and van Trijp 1991) acknowledge the contribution of SEM to the investigation of measurement issues and theoretical constructs. On the other hand, Freedman (1987), who challenges the usefulness of structural equations models, epitomizes the resistance movement. "In certain quarters, SEM is viewed with a fair amount of suspicion" (Steenkamp and Baumgartner 2000). Others (Brecker 1990; Cliff 1983; Fornell 1983) frown about the misuses of structural equations by the uninitiated (Baumgartner and Homburg 1996). SEM represents a different way of thinking that disrupts from traditional thinking (Bagozzi 1994; Steenkamp and Baumgartner 2000).

Since the mid-1980s, the number of marketing journal articles reporting SEM research has not skyrocketed. Most marketing papers refer to SEM for measurement models (i.e., confirmatory factor analysis), causal modeling, and for theory testing. Despite strong methodological foundations (e.g., Bagozzi and Yi 1989), few researchers employ SEM in experimental designs.

In 1980, Bagozzi brought causal modeling to the marketing research community (Baumgartner and Homburg 1996).

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Almost ten years later, Bagozzi and Yi (1989) persisted with the introduction of SEM to experimental design. Causal modeling with SEM gained in popularity, but experimental design applications did not see as much momentum. Bagozzi and Yi (1989) and Jöreskog and Sörbom (1989) showed that SEM could duplicate traditional analyses of variance.

This paper outlines the situations in which SEM presents potential methodological advantages over traditional analyses of variance (ANOVAs) and multivariate analyses of variance (MANOVAs). Bollen (1989, p. 2) argues that structural equations constitute a general model encompassing linear regression, simultaneous econometric equations, confirmatory factor analysis, canonical correlation, ANOVA, and analysis of covariance (ANCOVA). "All of these techniques—the whole of the GLM [general linear model], in fact—are in turn special instances of SEM" (Kline 2005, p. 14).

An ANOVA approach is suitable and adequate for examining group differences among measured variables, particularly when there are no hypothesized causality paths between dependant variables. With latent variables, sometimes tangled with mediating and moderating effects, SEM is preferable. Furthermore, ANOVAs focus on consumers' response to stimuli manipulations (stimuli-response [S-R] models). SEM has the capacity to measure behavioral responses as well as affective and cognitive processes leading to these behavioral responses (stimuli-organization-response [S-O-R]).

SEM REVISITED

Sewall Wright, who was a biostatistician, created path analysis models in the early 1920s and 1930s (e.g., Bollen

Journal of Marketing Theory and Practice, vol. 16, no. 4 (fall 2008), pp. 299–307.

ISSN 1069-6679 / 2008 $9.50 + 0.00.
DOI 10.2753/MTP1069-6679160403

1989, p. 4; Jöreskog and Sörbom 1989, p. 119). Econometric applications began spreading in the early 1970s. Researchers waited until the mid-1970s, with the advent of LISREL (Jöreskog 1973), to see significant application in the social sciences (Bollen 1989, p. 6). Structural equations' popularity paralleled the availability of the early versions of LISREL between 1975 and 1993 (Jöreskog and Sörbom 1989; 1993), EQS between 1989 and 1993 (Bentler and Wu 1993), and AMOS (Arbuckle 1989).

Only toward the end of the 1980s was SEM seriously considered as a complement or a substitute to ANOVAs for experimental data analysis. Bagozzi and Yi (1989) mention research works that go as far back as the 1970s. However, these were mostly theoretical and limited papers because the earlier software versions proved to be uneasy to use. Since then, constraints related to multigroup analyses and handling of categorical variables have been greatly relaxed.

From the General Model to Special Cases

SEM is part of the broad family of linear models. Hair et al. (2006) show algebraic similarities between the various forms of multivariate analyses with a dependent variable:

Multiple regression:

$$\begin{array}{ll} Y_1 & = X_1 + X_2 + X_3 + \ldots + X_n \\ \textit{Metric} & \textit{Metric} \end{array} \qquad (1)$$

Analysis of variance:

$$\begin{array}{ll} Y_1 & = X_1 + X_2 + X_3 + \ldots + X_n \\ \textit{Metric} & \textit{Nonmetric} \end{array} \qquad (2)$$

Multivariate analysis of variance:

$$\begin{array}{ll} Y_1 + Y_2 + Y_3 + \ldots\ Y_n & = X_1 + X_2 + X_3 + \ldots + X_n \\ \textit{Metric} & \textit{Nonmetric} \end{array} \qquad (3)$$

Structural equations:

$$\begin{array}{ll} Y_1 & = X_{12} + X_{12} + X_{13} + \ldots + X_{1n} \\ Y_2 & = X_{21} + X_{22} + X_{23} + \ldots + X_{2n} \\ Y_3 & = X_{31} + X_{32} + X_{33} + \ldots + X_{3n} \\ \ldots & = \ldots \\ Y_m & = X_{m1} + X_{m2} + X_{m3} + \ldots + X_{mn} \\ \textit{Metric} & \textit{Metric and nonmetric} \end{array} \qquad (4)$$

All forms of analyses of variance (ANOVA, ANCOVA, and MANOVA) are in the same GLM family as structural equations. Therefore, structural equation systems are appropriate for processing experimental data.

EXPERIMENTAL DATA ANALYSIS

Bollen (1989, p. 72) stresses two false beliefs about SEM. For a long time, it was believed that SEM was exclusive to nonexperimental (i.e., collected from observation). It was also believed that good experimental designs could avoid specification problems that are frequently encountered in SEM with observation data. Bollen (1989, p. 77) strongly argues that structural equations are applicable to both experimental and observational data. SEM has the capacity to shed a new light on problems that analyses of variance cannot test (MacKenzie, 2001).

Jöreskog and Sörbom (1989, pp. 112–116) first outlined the procedures for conducting ANOVA and ANCOVA using LISREL. Bagozzi and Yi (1989) provided additional examples for building MANOVA and MANCOVA (multivariate analysis of covariance) under LISREL and EQS.

Measurement Errors and Latent Variables

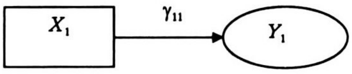
Apart from Bollen (1989), Bagozzi and Yi (1989, 1994) and MacKenzie (2001) are convinced that SEM clearly offers a more realistic methodological framework than simple or multivariate ANOVAs. Traditional analyses of variance approaches are limited to measured dependent and covariant variables without measurement errors (short of using composites). In the field of consumer behavior, as in the social sciences, this situation is not desirable. All measurements include random and systematic errors. Ignoring the latter either inflates or deflates coefficients (MacKenzie 2001). The measurement bias becomes even more important when experimental designs gain in complexity.

Cote and Buckley (1987, 1988) reviewed some 70 multitrait, multimethod studies. They note that nearly 42 percent of the observed variance was attributable to errors in constructs (traits). In the case of marketing research studies, variance associated with traits reaches close to 70 percent. It appears that researchers do not validate their constructs and minimize measurement errors. The two authors recommend multiple measures and confirmatory analysis for latent variables.

Consumer behavior research, either in a laboratory setting or in situ, is carried out around latent constructs such as beliefs, emotions, attitudes, satisfaction, brand loyalty, brand equity, materialism, ethnocentrism, need for cognition, personal involvement, and product knowledge (MacKenzie 2001). These constructs cannot be circumscribed from a single indicator. More so, summated rating scales do not resolve measurement errors because they assume that all items have the same weight. Finally, exploratory factor analysis cannot take into account measurement errors in each indicator reflecting single or multiple latent variables.

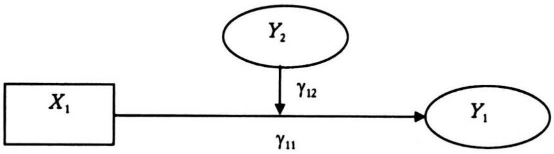
Specification Errors

Random allocation of subjects is one way to avoid specification errors with exogenous variables in experimental designs (Bollen 1989, p. 74). Other types of specification errors can easily sneak in, while undetected by analyses of variance. Let's take a look at some conditions reported by Bollen (1989), MacKenzie (2001), and Netemeyer at al. (2001). Equation (5) shows the effects of a manipulation (X_1) on Y_1, given $Y_1 = \gamma_{11}X_1 + \zeta_1$. An ANOVA will easily report the effect of X_1 on Y_1 but will ignore the measurement error on the Y_1 construct.



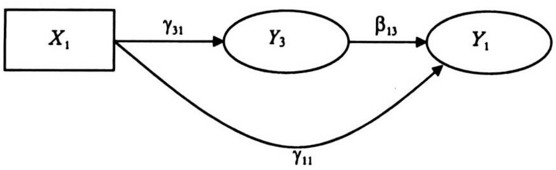
(5)

In Equation (6), Y_2 becomes a moderating variable such as $Y_1 = \gamma_{11}X_1 + \gamma_{12}X_1Y_2 + \zeta_1$. An ANOVA will capture the effect of X_1 on Y_1, and the interplay between X_1 and Y_2. It will not identify measurement errors associated with the covariate (Y_2) and the dependent variable (Y_1).



(6)

Equation (7) underscores the impact of X_1 both on Y_1 and Y_3. In this case, the Y_3 construct mediates the effect of X_1 on Y_1. If coefficient γ_{11} is significant, we should conclude that Y_3 is a partial mediator of X_1 on Y_1. Equation (7) then takes the following shapes: $Y_3 = \gamma_{31}X_1 + \zeta_1$ and $Y_1 = \beta_{13}Y_3 + \gamma_{11}X_1 + \zeta_2$. A MANOVA should recognize the dual influence of X_1 over Y_3 and Y_1. However, the MANOVA would not be able to identify simultaneously the effect of Y_3 on Y_1, or the role of Y_3 in the general model. This would have to be done in a separate step.



(7)

SEM has been applied to retail atmospheric experimental research where shoppers respond to myriads of environmental stimuli. Shoppers' response in stores and in malls involves complex cognitive, affective, and behavioral interconnections. Before the advent of structural equations, researchers manipulating environmental cues in the presence of several moderating and mediating endogenous variables relied on step-down MANOVA for controlling the order of effects, and regression analysis for testing mediation (Baron and Kenny 1986). SEM provides additional information not readily available in MANOVA. The following retail atmospheric examples illustrate how SEM tracks shoppers' complex processing of environmental cues.

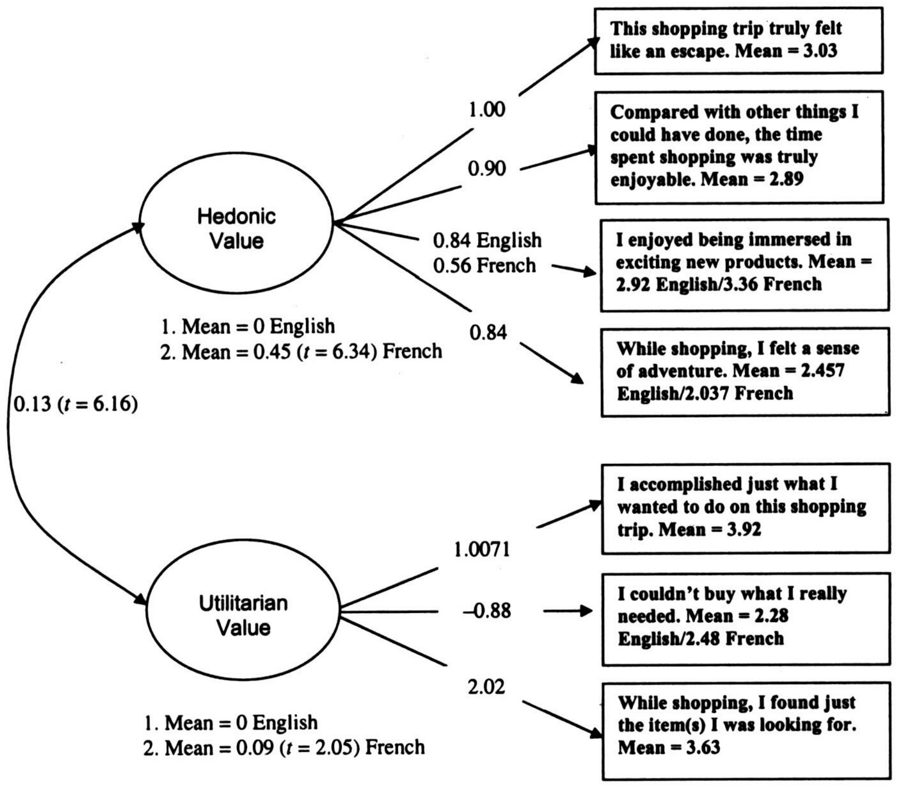
STRUCTURAL EQUATIONS AND QUASI-EXPERIMENTAL DATA

In quasi-experimental situations, exogenous variables cannot be controlled as effectively as in laboratory research. SEM can pinpoint specification errors and measurement errors better than MANOVA. Furthermore, SEM is exempt from balanced group size and homogeneity of variance requirements found in ANOVA. Michon and Chebat (2004) compared shopping values of English- and French-speaking consumers in a shopping mall. Some shoppers experience hedonic or experiential shopping benefits, whereas others are more likely to be utilitarian or task oriented (Babin and Attaway 2000; Babin, Darden, and Griffin 1994). A multigroup confirmatory factor analysis followed by a latent means comparison was seen as the most adequate methodology. The latent hedonic and utilitarian means for English-speaking shoppers were set to zero. Shopping values for the French cohort were compared against those of the reference group.

As shown initially by Babin and Attaway (2000), the hedonic and utilitarian constructs are not opposed, but positively correlated. The model depicted in Figure 1 demonstrates that constructs are quasi-invariant across both cultural groups; only one loading constraint has to be released. ("I enjoyed being immersed in exciting new products.") The adjustment statistics associated with the latent means analysis indicate that the model does need to be respecified (χ^2 = 148, degrees of freedom [df] = 31, comparative fit index [CFI] = 0.975, root mean square error of approximation [RMSEA] = 0.049). The structural equation model supports the hypothesis that French-speaking shoppers are more likely to exhibit hedonic values and achieve shopping objectives. The multigroup latent means structure does not only outline which cohort achieves higher hedonic and utilitarian scores but also where differences reside.

Shopping value dimensions are obviously latent constructs. In order to fit them in an ANOVA, researchers must resort to summated rating scales or factor scores derived from exploratory factor analysis. In both cases, measurement errors are generally ignored. ANOVA can tell if one group scores higher than the other on the hedonic or

Figure 1
Shopping Value of English- and French-Speaking Canadians
(Invariant Latent Mean Structures)



Notes: Chi-square = 148; degrees of freedom = 31; comparative fit index = 0.975; standardized root mean square residual = 0.053; adjusted goodness-of-fit index = 0.942; root mean square error of approximation = 0.049.

utilitarian value. However, it will have difficulty explaining where group differences come from without the help of a discriminant function or a canonical structure (Cole et al. 1993). Scale equivalence is a paramount issue in cross-cultural marketing (Myers et al. 2000). SEM simultaneously tests for measurement invariance and group differences on dependant variables. "There is essentially no other statistical procedure that does all of this" (Kline 1998).

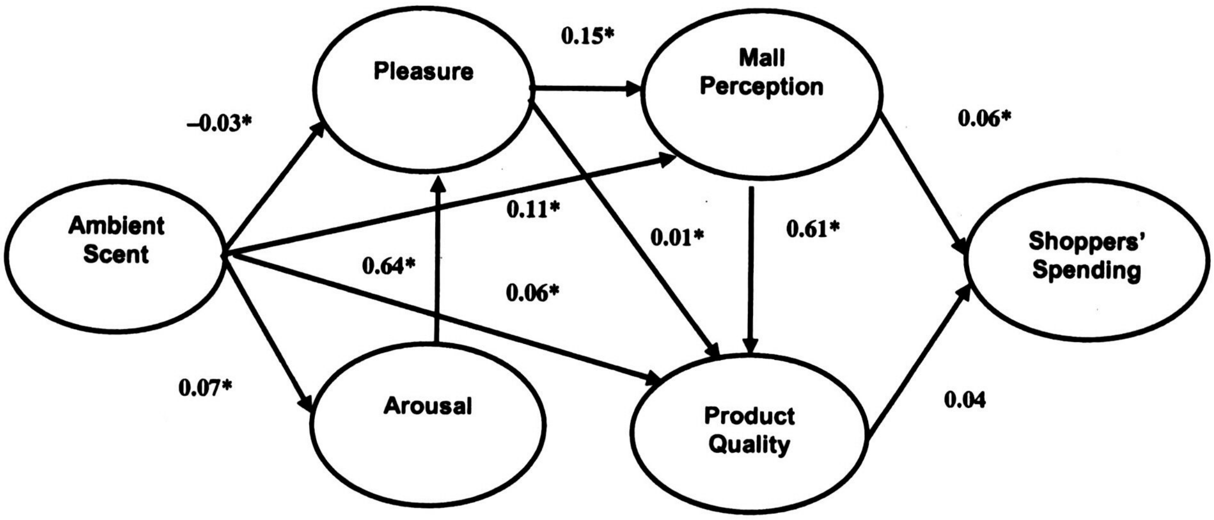
EXPERIMENTAL DATA AND THEORETICAL MODELS

Chebat and Michon (2003) tested the effect of ambient odors on mall shoppers against a control situation. The citrus odor was chosen because of its stimulating properties (Spangenberg, Crowley, and Henderson 1996). The effect of the ambient odor was tested on four different constructs: pleasure and stimulation (Mehrabian and Russell 1974), shoppers' perception of the retail atmosphere (Fisher 1974), and perception of product quality (Bellizi, Crowley, and Hasty 1983).

The environmental psychology theory (Donovan and Rossiter 1982; Mehrabian and Russell 1974) posits that the effect of retail atmospherics on shoppers' behavior is mediated by emotions. Previous research on ambient odors (Knasko 1992; Spangenberg, Crowley, and Henderson 1996) failed to demonstrate any mood shifts. Chebat and Michon (2003) tested two competing theories where (1) the ambient odor first transits through emotions before influencing shoppers' perceptions and behavior (e.g., Zajonc and Markus 1984), and where (2) the ambient odor is processed cognitively before affecting emotions and behavior (e.g., Lazarus 1991). Under both competing hypotheses, the four constructs represent endogenous variables (Figures 2 and 3). Ignoring measurement errors and mediating effects, a MANOVA is likely to estimate the impact of ambient odors on each of the four constructs but would not identify paths between the endogenous variables.

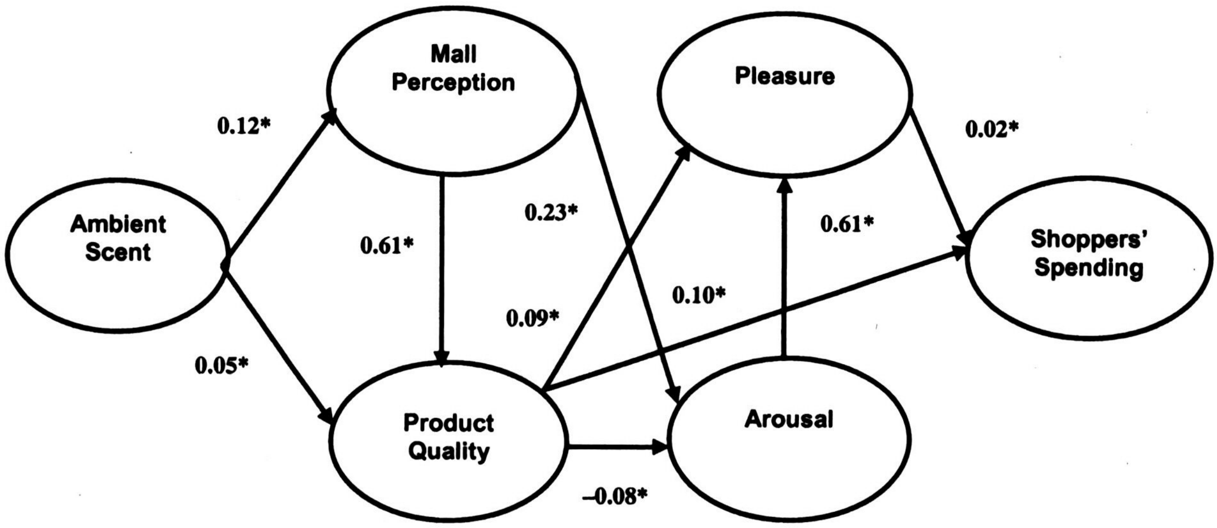
Fit statistics favor the cognition-emotion model (Figure 3: $\chi^2 = 36.52$; df = 63) over the emotion-cognition (Figure 2: $\chi^2 = 90.18$; df = 63). The ambient odor is initially processed through shoppers' perceptions of the mall environment and

Figure 2
Affect-Cognition Model: Emotion as an Antecedent to Cognition (Standardized Parameters)



Notes: Yuan–Bentler AGLS chi-square = 90.18; degrees of freedom = 63; $p = 0.014$; comparative fit index = 1.00. * Coefficients significant ≤ 0.05.

Figure 3
Cognition-Affect Model: Cognition as an Antecedent to Emotion (Standardized Parameters)



Notes: Yuan–Bentler (AGLS) chi-square = 36.52; degrees of freedom = 63; $p = 0.997$; comparative fit index =1.00. * Coefficients significant ≤ 0.05.

product quality. Perceptual constructs are antecedent to shoppers' emotions and behavior. The model suggests that a favorable perception of the mall environment (container) rubs off on the perception of product quality (content). It is also assumed that excitement is antecedent to the pleasure construct.

In the models shown in Figures 2 and 3, consumer spending has only one indicator, actual dollar disbursements during the shopping trip, excluding groceries. Its error variance has been set to 0. The presence or the absence of scent is represented by a dummy variable (1 and 0). Bagozzi (1994) and Bagozzi and Yi (1989) used dummy variables with structural equation models in experimental designs. Contrary to EQS, LISREL has to be tricked into accepting single indicators by creating pseudo latent variables with a coefficient set to 1 and the error variance set to 0. Because of nonnormal variables, both competing models were estimated with Yuan-Bentler (Yuan and Bentler 2002) corrected asymptotic general least square (AGLS) chi-square statistics, an asymptotically distribution-free statistic. Although MANOVA is relatively robust against nonmultivariate normality, asymptotic distribution-free methods in SEM remove the normality assumption, provided sample sizes are large enough.

Irrelevant of hypothesized causality paths, MANOVA would likely demonstrate the varying effects of ambient scent on the endogenous variables. Full or partial mediating effects would need to be tested one at a time through regression-type procedures (Baron and Kenny 1986). MANOVA would not have been able to describe how ambient odors lead to increased shopper spending. "Structural equation models allow for a more complete modeling of theoretical relations, whereas traditional analyses are limited to associations among measures" (Bagozzi and Yi 1989).

EXPERIMENTAL DATA WITH MODERATING AND MEDIATING EFFECTS

Consumers do not process atmospheric cues piecemeal, but holistically (Ward, Bitner, and Barnes 1992). Maximum retail effectiveness would be achieved when all environmental cues—ambient, design, and social—are congruent with the retailer's overall image (Baker 1998; Babin, Chebat, and Michon 2004). Furthermore, atmospheric cues interact with each other to produce unexpected effects. Kahn (1998) reports that an overstimulated environment may force consumers to simplify their purchase behavior and choose less variety. Babin, Hardesty, and Suter (2003) discovered that colors that seem counterproductive in a retail environment, such as orange, might produce favorable results in conjunction with other atmospheric parameters. Retail atmospheric cues can either be congruent for additive effects or interact with each other for unexpected effects.

Michon, Chebat, and Turley (2005) examined the interplay between ambient odors and physical density in a regional mall. Physical density is considered as a proxy for crowding construct. This is a 3×3 experimental design, with three stimulating odor intensities (control, lavender, and citrus) and three levels of commercial density (low, medium, and high). The ambient odors and physical density levels are, respectively, treatment and blocking factors. The selection of ambient odors is based on prior research by Spangenberg, Crowley, and Henderson (1996). Lavender is rated as pleasant but neutral on the arousing scale. Citrus is also perceived as pleasing but has more arousing power. In addition to the 3×3 factorial design, there are three dependant variables: pleasure or positive affect (Mehrabian and Russell 1974), shoppers' perception of the retail atmosphere (Fisher 1974), and the perception of product quality (Bellizi, Crowley, and Hasty 1983). Rather than reverting to a MANOVA with two factors, the effect of ambient odors in conjunction with retail density is tested using a multigroup structural equation model (Figure 4). The ambient odor manipulation is shown as a discrete variable (low to high arousal, assuming an asymptotic distribution).

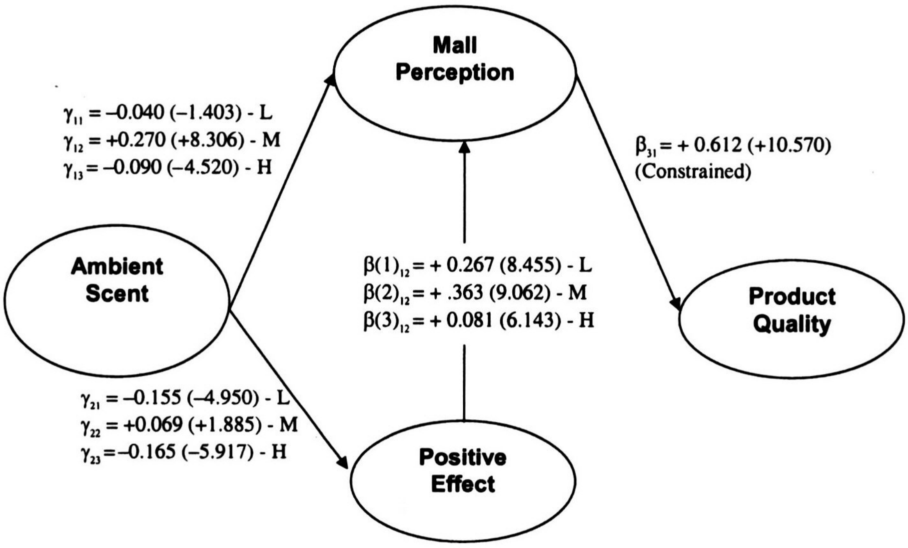
The fixed paths across all three groups linking ambient odors manipulations, positive affect, and mall perception must be rejected. The arousing effect of ambient odors on shoppers' positive effect and mall perceptions is only observed under the medium-density condition. In low and high physical traffic, arousing ambient scents have a negative effect on both emotion and mall perception constructs. The multigroup model is the simplest way to underscore the nonlinear interplay between ambient odors and retail density.

The influence of ambient odors on mall perceptions is partly mediated by shoppers' positive effect. Shoppers' perception of the mall environment has a direct impact on the perception of product quality. Shoppers' emotion only has an indirect effect on the perception of product quality. The structural equation coefficients highlight the interaction effect between ambient scent and retail crowding (Figure 5). A MANOVA would show the significant relationship between the experimental manipulation and the perception of product quality, as well as the interaction effect with retail crowding. The SEM not only pinpoints the interaction effect between ambient odors and retail density on shoppers' emotion and perception but also isolates mediating effects and antecedents, something that MANOVA cannot do in one step. In addition, the use of MANOVA on reflective latent variables can be misleading (Cole et al. 1993).

OPENING UP THE "BLACK BOX"

SEM has not made ANOVA and MANOVA obsolete. There are numerous circumstances where ANOVA is both effective and parsimonious. Furthermore, marketing managers are more likely to be familiar with traditional analyses of variance than using multigroup latent means analyses. Researchers

Figure 4
Multigroup Retail Density and Ambient Scent Manipulation (Standardized Coefficients and Model Adjustment Statistics)



Notes: Chi-square = 99.645; degrees of freedom = 107; Pr = 0.68; Yuan–Bentler AGLS chi-square = 44.68; comparative fit index =1.00; root mean square residual = 0.062; root mean square error of approximation = 0. L/M/H = low, medium, and high retail density.

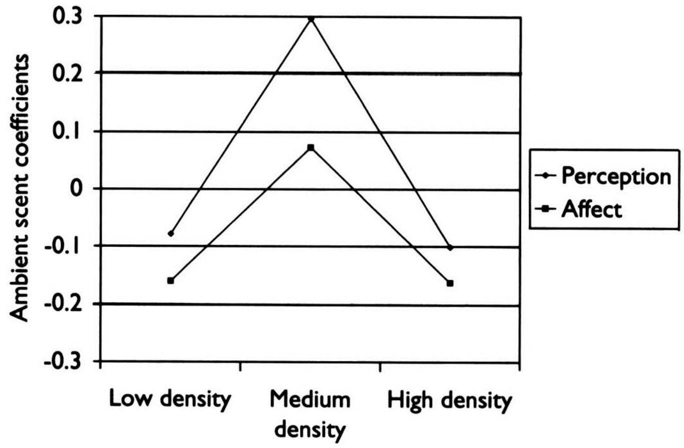
working on behavioral S-R models find that ANOVA will do the job. There is no need for SEM when working with single indicator constructs and measured variables. Finally, ANOVA can accommodate much smaller sample sizes than SEM.

Analyses of variance identify significant effects, and structural equation models show how effects take place. Marketing researchers using experimental data often want to understand the cognitive and emotional processes underlying consumers' behavior. They also attempt to open up the "black box" rather than just look at the behavioral responses to experimental manipulations.

SEM has some relative advantages over traditional analyses of variance. The SEM methodology is clearly less restrictive than ANOVA in reference to between-group variance and covariance homogeneity assumptions for dependent variables. It also allows for measurement error corrections and offers a better theoretical explanation of models (Bagozzi and Yi 1989). Formerly, SEM imposed more constraints on multivariate normality. With the development of new algorithms, SEM has become more tolerant to nonnormality but requires larger samples.

The adoption of SEM was greatly enhanced with the advent of user-friendly applications. The development of new fit and adjustment indices reduces the probability of Type I and Type II errors, while taking models away from excessive chi-square statistics sensitivity (MacKenzie 2001). Yet

Figure 5
Ambient Scent and Retail Density Interplay (Path Coefficients on Shoppers' Perception and Affect)



models are not exempt from structural aberrations. Mittal (1993), for example, shows how easy it is to inverse causality path directions while maintaining the same model fit. It emphasizes the need for researchers to design experimental models solidly anchored in theory, in the literature, and in previous empirical research.

The use of structural equations forces researchers to conceptualize their experimental models beyond the S-R approach. The benefits derived from SEM with experimental data constitute a better approach to modeling consumer behavior and, in general, a better way to theory building in social sciences and in marketing. For example, in addition to shoppers' response to retail atmospheric manipulations, SEM analysis outlines the importance of cognition (shoppers' perception) over affect. Retail atmospheric cues do more than influence shoppers' mood; they communicate meanings about the retail environment and the perception of product quality. The knowledge of emotional and cognitive drivers underlying shoppers' behavioral response will help researchers better understand how environmental cues are processed, generalize findings, and fine-tune the environmental psychology theory.

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