HEALTH COMMUNICATION, *20*(2), 159–167

On the Use of Structural Equation Modeling in Health Communication Research

Michael T. Stephenson
Department of Communication
Texas A&M University

R. Lance Holbert
Department of Communication
University of Delaware

Rick S. Zimmerman
Department of Communication
University of Kentucky

Structural equation modeling (SEM) is a multivariate technique suited for testing proposed relations between variables. In this article, the authors discuss the potential for SEM as a tool to advance health communication research both statistically and conceptually. Specifically, the authors discuss the advantages that latent variable modeling in SEM affords researchers by extracting measurement error. In addition, they argue that SEM is useful in understanding communication as a complex set of relations between variables. Moreover, the authors articulate the possibility for examining communication as an agent, mediator, and an outcome. Finally, they review the application of SEM to recursive models, interactions, and confirmatory factor analysis.

Health communication researchers need an arsenal of theoretical, methodological, and data analytic skills to see a research project through from start to finish. While there exist an array of resources for theory and methodology (Crano & Burgoon, 2002; Hornik, 2002; Maibach & Parrott, 1995; Miller, Alberts, Hecht, Trost, & Krizek, 2000; Rice & Atkin, 2001; Thompson, Dorsey, Miller, & Parrott, 2003), health communication scholars for the most part have shied away from writing extensively about data analytic skills and strategies (cf. Hornik, 2002; Valente, 2001). Therefore, we are enthusiastic about this opportunity to present structural equation modeling (SEM) as a data analytic approach suitable for some health communication research.

Although SEM is certainly not new (e.g., Jöreskog, 1967, 1969), its diffusion into communication research is more recent. Cappella (1975) wrote the first article introducing the topic to the discipline, but nearly a decade passed before McPhee and Babrow (1987) discussed the uses and misuses of the technique. The development of computer technology brought both processing power and user-friendly programs that facilitated the use of the technique. This was a mixed blessing according to Holbert and Stephenson (2002, 2003; Stephenson & Holbert, 2003), who provided a series of reviews of communication-based SEM research in order to facilitate the proper use of the technique.

In this article, our purpose is to explain how scholars of health communication can take advantage of this versatile multivariate tool to advance both their research agendas and their understanding of health communication. In this essay, we aim to (a) provide a brief description of SEM, (b) present the statistical advantages of this technique for health communication research, (c) demonstrate how SEM informs our understanding of communication as a process, and (d) provide examples of how SEM advances research in health communication. Note that we do not present a primer on SEM. Such a task is not feasible in one article, and there exist other excellent sources that already provide this information (e.g., Bollen, 1989; Hoyle, 1995; Kaplan, 2000; Kline, 1998; Loehlin, 1998; Maruyama, 1998; Raykov & Marcoulides, 2000). Instead, we focus on SEM as an analytical tool that

Correspondence should be addressed to Michael T. Stephenson, Department of Communication, Texas A&M University, 4234 TAMU, College Station, TX 77843-4234. E-mail: mstephenson@tamu.edu

can advance our knowledge of health communication as a set of interrelated variables that define communication as a process. We hope to whet the appetite of readers in a way that motivates them to pursue additional knowledge of this technique. We proceed with one caveat: SEM is not appropriate for all research endeavors, and it is the researcher's decision to determine the data analytic technique most appropriate for addressing his or her hypotheses and answering research questions. Our overview below will provide the reader with an indication of when SEM is useful to consider as a data analytic tool.

OVERVIEW OF SEM

SEM is used to estimate simultaneously a system of hypothesized relationships among observable and latent variables to determine whether these associations are consistent with an obtained sample of data (Bollen, 1989). This multivariate analytical technique emerged from three separate lines of mathematical and statistical analysis: path analysis, factor analysis, and simultaneous equation modeling. Wright (1934) offered the first breakthrough in path analysis by demonstrating how the associations among variables are related to model parameter estimates that take the form of a path diagram (Kaplan, 2000). As Wright was refining his method of path analysis, Thurstone (1947) was advancing the study of factor analysis (see Mulaik, 1972, for a review). Similarly, individuals in the field of econometrics began developing and refining a technique of simultaneous equation modeling (see Blalock, 1971). The work of Karl Jöreskog bridged these three areas (Cudeck, du Toit, & Sörbom, 2001). His earliest contribution in the development of SEM, confirmatory factor analysis (CFA; Jöreskog, 1967, 1969), linked previous work by Lawley on maximum likelihood and restricted factor analysis to create the basic measurement tool that is common to all major SEM programs (i.e., LISREL, EQS, AMOS; Jöreskog & Lawley, 1968). However, the present-day technique has evolved beyond the study of just measurement models to become "a melding of factor analysis and path analysis" (Kaplan, 2000, p. 3). Indeed, SEM has been called "the single most important contribution of statistics to the social and behavioral sciences during the past twenty years" (Lomax, 1989, p. 171).

There are two common components to a structural equation model: the measurement model and the structural model. The measurement model analyzes relationships among a set of observable variables and a predetermined number of latent variables. Observable variables are those collected in the researcher's measurement instrument, while latent variables exist beyond human measurement. The use of latent variables cannot be overemphasized because, "All observation is fallible, no matter how refined the measuring instrument… we never measure exactly the true variables discussed in our theories. In this same strict sense, all (true) variables are 'unobserved'" (Duncan, 1975, p. 113). The associations among the observable variables and latent variables in a model are established a priori and tested against a data set to see if the hypothesized measurement relationships match the data that have been collected. Beyond the associations analyzed by the measurement model, the structural component of the model analyzes a series of a priori relationships established between latent variables. The structural component of the model can also analyze relationships among observable variables if a researcher is treating all single items or additive indexes as observable. The latter scenario is oftentimes referred to as *path analysis* (Kline, 1998), but SEM-based analyses of this type are distinct from earlier forms of path analysis given the more common use of full-information estimation procedures in SEM software.

There are three primary steps in SEM: specification, estimation, and evaluation. Specification involves (among other things) identifying the set of relationships one wants to examine, determining how to specify these variables within the model (see Stephenson & Holbert, 2003), and screening the data set so that it adheres to the assumptions of the statistical theory underlying SEM analyses. Estimation is the "first logical step" that follows specification (Chou & Bentler, 1995, p. 37). In this step, researchers make decisions about what data structure will be used (i.e., covariances, correlations, or raw data), partial- versus full-information estimation procedures, and how to evaluate the hypothesized model against a data set. Finally, model evaluation pertains to goodness of fit, multivariate normality, and model modification, if warranted. There is much more to these three steps than we can provide here. Our point is that it is only after all three steps (specification, estimation, and evaluation) have been completed with sufficient methodological rigor that a researcher can make judgments about the hypotheses that served as the basis for creating the structural equation model.

STATISTICAL ADVANTAGES TO SEM

Perhaps the principal advantage of SEM is the ability to model constructs as latent variables. This affords researchers the opportunity to extract measurement error. Once measurement error has been extracted from the latent variables that have a specified relationship in a model, only the systematic relationship between these latent variables remains (Cudeck et al., 2001; Jöreskog, 1973). Before we proceed, let us clarify that a latent variable is an underlying construct not directly tapped by any one set of measures, although the typical process is to capture the construct by measuring it with multiple items (Duncan, 1975). For example, consider sensation-seeking. It is a latent construct and we choose to capture its meaning by measuring it with a 4-item scale (Stephenson, Hoyle, Slater, & Palmgreen, 2003).

In latent variable modeling, a construct's unreliability is accounted for in the measurement model. The measurement model consists of measured variables and their respective error terms, latent variables and their error terms (also called disturbance terms), and the relationships between the measured and latent variables. The error terms for measured variables estimate the unreliability (measurement error) that exists between the measured and latent variables. The disturbance term for the latent variable represents the variance unaccounted for in the latent variable by the measured variables. "In this way, uniqueness and random error are divorced from commonality in such a way that the reliability… is in effect 1.0" (Hoyle & Kenny, 1999, p. 203). As a result, the parameter between the measured variables and their respective latent variable reflects the systematic (true) relationship of measurement corrected for unreliability (see Bollen, 1989, pp. 218–221 for a detailed discussion).

Allow us to illustrate with a very simple example that involves examining the correlation coefficient between two scales, sensation-seeking and attitude toward marijuana use. If sensation-seeking is measured with a four-item scale and attitude toward marijuana is measured with a three-item scale, protocol is to use SPSS or SAS to first examine the reliability of each scale individually. If they are reliable, we compute the mean for each scale and then generate the correlation between the two variables. The correlation is reported in the output. Unless the reliability of the two scales is 1.0, this correlation coefficient is attenuated by measurement error (Schmidt & Hunter, 1996). In contrast, if we use SEM procedures, we can model these two constructs as latent variables. This implies that the four items for the sensation-seeking scale would "load" on one latent variable and the three items for attitude toward marijuana would load on the other latent variable. Provided that we followed the correct procedures, the SEM program would extract the measurement error from both constructs (where measurement error is a function of the construct's reliability) in order to provide the unattenuated correlation between sensation-seeking and attitude toward marijuana use. The more measurement error (i.e., the lower the reliability) in each construct, the more the correlation between them is affected. Although this is a very basic example, one can see that SPSS or SAS (or your favorite statistical software) will not extract measurement error because they do not model constructs as latent variables. Structural equation software *can* model latent variables and extract measurement error. This is the unique advantage of using latent variables in SEM.

Eliminating measurement error is important in health communication research. First, statistically speaking, the effect of most health interventions is comparatively small. For example, Snyder's (2001) meta-analysis indicated that approximately 12% of the specified target audience changed their behavior as a result of a communication campaign encouraging new behaviors. Meanwhile, Derzon and Lipsey (2002) concluded, in their meta-analysis of antidrug campaigns, that adolescent drug use would be 1% to 2% lower as a result of media substance abuse campaigns. Second, because typical effect sizes are already modest, allowing measurement error to manifest itself in critical outcome variables will only continue to mask the true (and perhaps already small) effect. "Random error of measurement distorts virtually every statistic computed in modern studies" (Schmidt & Hunter, 1996, pp. 199–200). Because many health interventions are field experiments where measurement error is sure to abound, the intervention effects are likely to be modest. It is therefore justified for researchers to use available statistical procedures to eliminate the effects of measurement error in order to reveal the unattenuated, systematic effect of the health communication intervention on behavior. One way we can capture and remove it, then, is with SEM. In most instances (although not all, see Bollen, 1989), removing measurement error results in comparatively larger effects.

CONCEPTUAL ADVANTAGES TO SEM: HEALTH COMMUNICATION AS A PROCESS

Although there exist many viable ways to analyze health communication data, SEM is particularly useful in allowing researchers to visualize, and therefore analyze, communication as a process. Cappella (1991) writes that "processes … are the guts of any substantive theory" (p. 168), and that "how messages are understood (read, interpreted, comprehended, etc.) is a process question fundamental to all forms of human communication" (p. 169). Not only do we fully endorse Cappella's viewpoint, but we would also argue that SEM is a statistical tool that provides researchers with a unique opportunity to explore these processes.

This argument, in part, hinges on the notion that SEM allows one to analyze simultaneously a system of equations that represent a theoretical process (i.e., Duncan, 1975). Underlying the analysis of these systems of equations is full-information maximum likelihood estimation, an iterative feature of the statistical software that determines if the hypothesized model is consistent with the observed data (i.e., whether the model fits). This approach is in direct contrast to traditional general linear model (GLM)-based approaches such as multiple regression. These statistical analyses employ partial-information ordinary least squares estimators that solve systems of equations one by one, not as a system of equations that can be solved simultaneously (Ahmed & Mosely, 2002). Sometimes researchers will employ regression to generate a path analysis, but the process of obtaining this analysis is simply a function of running a series of regressions in SPSS, SAS, or another statistical package. The latter does not estimate the entire theoretical model (or process) but instead tests sections of the theoretical model (or process) one at a time. Therefore, there is no joint, systematic evaluation of the omnibus theoretical model, an approach that is available in SEM through full-information maximum likelihood (and other) estimators (Blalock, 1971; Bollen, 1996; Jöreskog, 1973).

Moving health communication research forward, then, includes understanding the complexity of the communication process. In that vein, Parrott (2004) argues that "Communicating about health implicitly reflects multiple discourses but usually only explicitly addresses one component at a time. … Seemingly too little progress has been made to address this issue directly" (p. 774). We agree. By failing to consider the broader network of variables, modeled simultaneously to understand the complexity of relationships involved in communication, we cannot thoroughly understand the role communication plays within a larger nomological network.

Viewing communication as a process means fully testing theoretical models rather than analyzing small or discrete sections of them one by one (as is the limitation of GLM analyses). Mongeau and Stiff (1993) made this argument for research on the elaboration likelihood model (ELM; Petty & Cacioppo, 1986), specifically that social scientists had relegated tests of the model to a series of analyses of variance, thereby failing to consider the explanatory and predictive features of the omnibus theoretical model. More important, however, is that researchers were missing the opportunity to analyze a system of relationships theorized by the ELM that were ideal for testing with SEM (see Stephenson, Benoit, & Tschida, 2001).

We see an almost identical situation in health communication with Witte's (1992, 1994) extended parallel process model (EPPM). Despite its considerable contribution to the health communication literature, as evidenced by the number of studies that use it (see Witte & Allen, 2000), we have yet to see a test of the EPPM as an omnibus structural model assessing the relationships between variables (Witte, personal communication, February 26, 2006).[1] Instead, researchers have focused more on the divergent outcomes (danger control processes or fear control processes) that are a function of various message features (threat and efficacy), and researchers have analyzed their data in these studies within the GLM-based framework (e.g., Stephenson & Witte, 1998; Witte, 1994). Certainly this is helpful in understanding that one type of message has these effects under certain conditions. But the bigger issue, from an SEM standpoint, is that the EPPM is proposed theoretically (and graphically) as a set of structural relations between variables. Hence, the untested omnibus theoretical model remains an opportunity for exploration.

Opportunities also exist for understanding and advancing our knowledge of communication within patient–provider relationships. Although his model is fundamentally different from Witte's model in both scope and context, Street (2003) advances a three-stage framework describing the process of patient interaction with health communication technology. In describing the utility of his model, Street (2003) formally advances our argument, claiming that those who research patient–provider communication "have done relatively little to develop and test theoretical models of the processes underlying these interactions" (p. 63). Consequently, Street introduces the three stages of his framework: implementation (comprised of institutional, technological, and user factors), which influences use (utilization of technology and intermediate outcomes such as knowledge and efficacy), which then affects health outcomes (health improvement, lifestyle change, preventive action). Street argues that there are important communication variables that influence each stage of the relationship. The model is an elegant portrayal of a complex process where communication is central to a set of relationships with other noncommunication variables. Certainly one could take various components of the model and examine them separately. Depending on one's research interests, this may certainly be a reasonable and justified approach. But to the extent that someone wants to fully understand the role of communication within the process of relationships implicated in Street's model, SEM can be a means toward that end.

Beyond patient–provider frameworks, understanding communication as a process is important to other health communication contexts. Albrecht and Goldsmith (2003) identify social support as a "process embedded in structures of ordinary relationships in social life" (p. 263). Mass communication campaigns are no different, as "much of the history of research in health education and communication … is the story of implementing and evaluating interventions" (Hornik, 2002, p. 15).

Health communication researchers, then, agree that communication is a process within various contexts. The issue at hand, then, is to move our research in the direction of analyzing communication as a process involving a host of other variables. To the extent that theoretical models present communication as a process, or alternatively as one part of this process, SEM is well suited to help accomplish this task. The primary advantage in modeling these processes is that SEM uses full-information estimation procedures that allow a greater set of theoretical relationships (i.e., systems of equations) to be analyzed simultaneously.

CONSTITUTING COMMUNICATION AS AN AGENT, MEDIATOR, OR OUTCOME

To consider communication as a process, one must theoretically derive where in the path model the communication component would reside. The communication component may be studied as the stimulus and thereby located on the far left-hand side of the structural model (i.e., as agent of influence). Alternatively, communication may be located in the middle of a model, functioning both as a response to previous stimuli but also activating subsequent outcomes as well (i.e., as mediator). Finally, communication may be examined at the far right-hand side of the model as the primary dependent

[1]Murray-Johnson, Witte, Boulay, et al. (2001) test a portion of the EPPM, although the nature of the secondary data analysis meant that some critical variables were not included in the model's estimation.

endogenous variable (i.e., as outcome). First, let us consider communication as agent.

In communication campaign research, we often measure exposure to some form of communication and evaluate the effects of this communication. When communication is the stimulus, it can be used as an exogenous variable in a structural model (that is, the left-most variable in the model, from which the first set of relationships between the variables emerges). For example, Evans et al. (2004) examined the impact of exposure to antitobacco ads on tobacco independence, social imagery, and smoking status. In their model, then, exposure was the communication variable that acts as the agent of influence. Or, consider research by Dillard and Peck (2000) that tested the effects of six public service announcements on the emotional responses of viewers. Because separate models were generated for each of the six ads, the authors did not need to model exposure on the far left-hand side of the model. But in this circumstance, the important point is that message exposure functioned as the agent instigating the communication process that they studied.

A second way to understand communication as a process is to examine communication as a mediating variable. Under these circumstances, a stimulus or exogenous variable would influence a communication variable, which in turn would affect some outcome variable. Slater and Rasinski (2005) recently wrote that the "conceptualization and analysis of media influences on outcomes such as risk judgments should explicitly recognize that media use patterns are largely the result of and therefore should at least partially mediate the effects of exogenous variables such as demographics and prior experience" (p. 811). Under these circumstances, media exposure and attention are both a result of and an antecedent to noncommunication variables. Understanding communication as a mediating variable suggests that, at least in the previous scenario, interpreting one's risk judgments solely based on demographic and previous experience alone is incomplete without considering the role of the media.

If we specify communication variables as either agent or mediating, it provides us with a unique opportunity to understand both the direct and indirect effects of communication variables on outcome variables (Holbert & Stephenson, 2003). Unfortunately, as a discipline, we have not done a very good job of considering the indirect effects of communication variables. From 1995 to 2000, only one in seven articles using SEM in communication research considered the direct, indirect, and total effects of the communication variables within a broader structural model (Holbert & Stephenson, 2003). McGuire (1986) warned us 2 decades ago that we have a misguided fixation on the direct effects of communication variables. By not assessing indirect effects, the discipline is systematically underestimating the overall influence of communication in a number of contexts. For example, in Austin and Chen (2003), parental mediation (the communication component) is found to influence alcohol consumption, but the impact of parental mediation is indirect through desirability, skepticism, and alcohol expectancies. Without considering the critical mediating variable in the process, the total effects of parental mediation on alcohol consumption would be substantially less and obscure.

Decomposing the effects reveals a much more complete understanding of communication as a process and moves the discipline beyond the study of direct effects only. Moreover, there is recent research that substantially advances our ability to analyze indirect effects. It is an advantage that SEM allows one to specify relationships between multiple variables. But, as discussed in Holbert and Stephenson (2003), neither the traditional requisites for mediation articulated by Baron and Kenny (1986) nor the statistical requirements for mediation, as advanced by Sobel (1982), can be easily implemented in multivariable structural models. This issue is complex, but we do present the issue of mediation, direct, indirect, and total effects and the confidence intervals for these estimates in more detail elsewhere (see also MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002; MacKinnon, Lockwood, & Williams, 2004).

A third way to understand communication as a process is to consider it as an outcome variable. Research on partner communication (typically described as "negotiation") about condom use or safer sex, for example, has used partner communication about safer sex both as a predictor of other outcomes (e.g., condom use), and as an outcome variable, in research that views correlates or predictors of partner communication about safer sex. An example of the latter is an article by Noar (2003), in which he first describes the process utilizing SEM to develop a scale. Noar then assesses the impact of condom self-efficacy, negotiation self-efficacy, stages of change, sexual assertiveness, supportive partner communication, and sexual communication about other topics on the use of six condom influence strategies or negotiation strategies (viz., withholding sex; making a direct request; "seduction," in which nonverbal cues are used; indicating caring or concern for the partner, or "relationship conceptualizing," presenting information about the risk of STDs or AIDS; or deception). Results indicate that condom self-efficacy, stage of change, and sexual assertiveness were significantly and positively related to use of nearly all of the condom influence strategies, whereas results for supportive partner communication and sexual communication were weak or mixed.

ADDITIONAL USES OF SEM

Nonrecursive Models

Understanding communication as agent, mediator, and outcome is a useful heuristic, but it does not directly speak to the notion that the process is affected by a feedback loop. To understand the process fully, then, we must also consider whether a structural model can theoretically be specified as recursive or nonrecursive. A process of influence need not move simply from left to right within a model (i.e., a basic recursive model). Reflecting more complex processes, "nonrecursive models contain reciprocal causation, feedback loops, or they have correlated disturbances" (Bollen, 1989, p. 83). The most common form of nonrecursive model found in the field contains correlated disturbances. Two latent variables are often allowed to freely covary in a model when a significant, nonzero relationship exists between the two latent constructs, and the researcher cannot determine the causal nature of the relationship between the two variables. This type of nonrecursive model is the least theoretically interesting because it is most often created based on what a researcher does not know (i.e., nature of causal direction) rather than on what can be properly hypothesized. Nonrecursive structural models that hypothesize reciprocal relationships or feedback loops reflect greater theoretical sophistication. Health communication researchers need to be aware that they can step outside the relatively limited scope of testing purely recursive models; SEM allows for the testing of more sophisticated theoretical arguments.

Interactions and Structural Models

Interactions between variables are common in health communication research. Some research on message effects examines the interaction between sensation seeking and message sensation value (Everett & Palmgreen, 1995), while other research on fear appeals specifies an interaction between threat and efficacy (Witte, 1992, 1994). In both cases, the interaction has implications for the effects of the message on the recipient.

Unfortunately, SEM analyses have historically lacked an established technique through which to assess interaction effects (Schumacker & Marcoulides, 1998). Three techniques, all with inherent strengths and weaknesses, have become commonplace in the SEM literature. Schumacker and Marcoulides define these techniques as the following: multiple-group, product indicant, and nonlinear.

The multiple-group approach is suitable when the moderator variable is discrete and categorical. A multigroup model is tested and a specific parameter estimate is compared across groups. For instance, Stephenson (2003) used sensation seeking as a moderator to analyze a multigroup model. Once the theoretical model was specified, he analyzed the relationships in the model for high and low sensation seekers separately. The outcomes indicated that the pattern of relationships between cognitive and affective variables on antidrug attitudes was considerably different for high and low sensation seekers.

The more cumbersome product indicant procedure is used when the moderator variable is a multiple-indicator latent variable. A new latent interaction variable is created within a model by multiplying pairs of observed variables that are indicators of the respective latent constructs involved in forming the interaction. There are multiple ways by which to form the latent product-indicant variable, either using all indicators or a sample of observable items (the latter is used when the original latent variables consist of a large number of items). The nonlinear technique replaces the traditional linear estimate with a nonlinear estimate (i.e., cubic, quadratic). Schumacker and Marcoulides (1998) detail the strengths and limitations of each procedure.

A recent advance provides a fourth technique for testing interactions in structural equation models: latent variable scores. This approach is detailed fully by Schumacker (2002), and the means by which to compute latent variable scores in LISREL is outlined in Jöreskog, Sörbom, du Toit, and du Toit (1999). The computing of a latent variable score yields a single latent construct that generates a relatively simple model structure when compared to the latent interaction variables typically created with the product-indicant approach. Schumacker (2002) finds the latent variable score approach "easier to implement" than the product-indicant method. In addition, "the latent variable approach also has utility when testing more complex structural equation interaction models" (p. 49).

Measurement and Confirmatory Factor Analysis

Thus far, we have focused on the structural component of the model, where the structural model comprises the relationships (i.e., paths) between latent variables. However, it is important to remember that SEM also allows one to conduct a confirmatory factor analysis (CFA) in order to evaluate the measurement properties of the model. Anderson and Gerbing (1988) advocate a two-step procedure where researchers first establish that the measurement of the latent construct is consistent with the theoretical structure imposed on the data. This step should occur prior to estimating the structural component. This procedure, called CFA, is where one tests a set of theoretical relationships between measured variables and their respective latent constructs.

Perhaps the primary benefit of CFA to health communication scholars is that it helps us understand the empirical properties of theoretically guided constructs for our research. CFA allows researchers to advance and test the measurement properties of a scale or its subscales a priori. This is important because the conclusions of our research are only as good as the measurement of the concepts used in the research.

We can illustrate CFA with this with an example from Lane, Harrington, Donohew, and Zimmerman (in press), who set out to develop a new scale to measure the perception of message cognition value (MCV), a construct designed to guide the development of specific message content characteristics capable of enhancing the cognitive processing of persuasive messages (Harrington, Lane, Donohew, & Zimmerman, 2006). MCV is a message counterpart to need for cognition (Cacioppo, Petty, Feinstein, & Jarvis, 1996). But because MCV is a new message strategy, a scale evaluating subjective responses to this strategy was warranted in order to provide empirical evidence behind its conceptual development.

Therefore, Lane et al. (in press) set out to develop and validate an instrument for assessing the perceived message cognition value (PMCV) of persuasive messages in health communication interventions. In developing the scale, the authors first reviewed the persuasion literature to identify words and phrases consistent with the construct of message cognition value. When this review was complete, the authors had a list of 54 potential items to use in developing this scale. Following a series of exploratory empirical assessments, the authors retained 13 of the original 54 items. These 13 items fell into a meaningful structure of three factors: cognitive challenge, clarity, and credibility.

What was unclear to this point was whether the 13 items comprising these three factors were empirically unique to their respective three factors. Therefore, the authors conducted a CFA using the SEM program AMOS. They specified that 5 of the 13 items loaded or comprised the latent variable representing cognitive challenge, 5 items loaded on clarity, and 3 items loaded on credibility. After comparing a series of nested models (a procedure used to determine which model is the most accurate empirical representation of the data), they concluded that the model representing the new PMCV scale was in fact consistent with the data.

Figure 1 presents the recently validated PMCV scale. Note that the data are most consistent with a second-order factor model, confirming that the PMCV retains a multidimensional structure. Combined with Cronbach's alpha coefficients of .75 or higher for both the composite 13-item scale

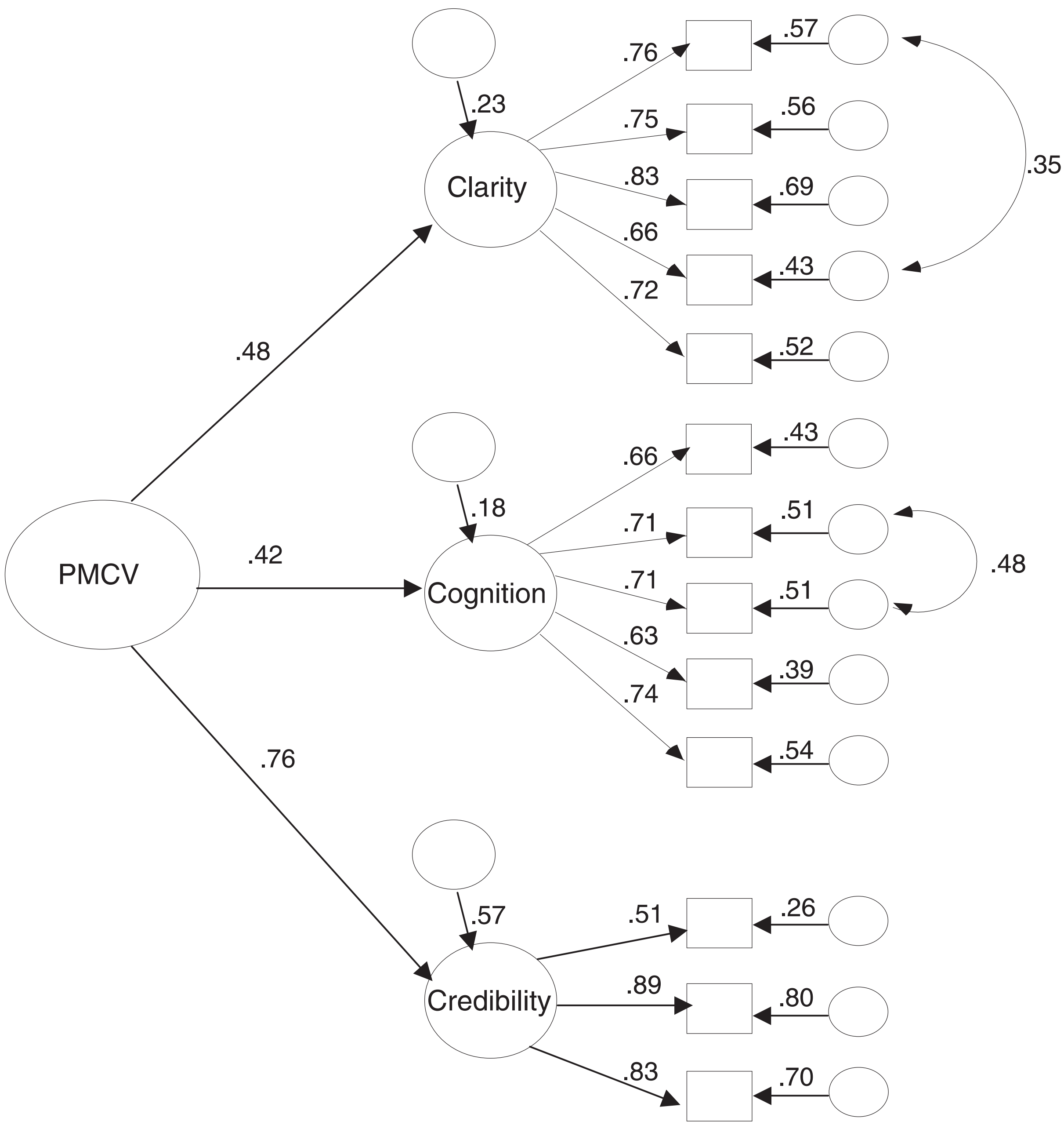

FIGURE 1 Measurement model for confirmatory factor analysis.

and the three subscales, these results suggest that the overall PMCV scale is sufficiently reliable and the three subscales can also be reasonably considered to be reliable subcomponents of the overall scale.

CONCLUSION

Our enthusiasm for SEM is based on its ability to advance our understanding of communication as a process. Communication is complex and it does not occur as an isolated incident (Parrott, 2004). This certainly is no different for health communication phenomena. Moreover, measurement of communication and other theoretically important variables will be laced with both systematic and random error (Schmidt & Hunter, 1996; Stephenson & Holbert, 2003). It is an advantage, then, that with SEM we can isolate random error and extract it so that it does not artificially mask the relationships between variables of interest (Hoyle, 1995). Finally, SEM provides a way for us to understand communication as a direct or indirect effect, as well as the extent to which moderating variables shape the communication process (Holbert & Stephenson, 2003).

SEM is not without its critics (Breckler, 1990; Cliff, 1983) or problems, and we would not suggest otherwise. SEM is fallible. Therefore, we encourage scholars to understand how SEM might advance a particular research program in ways in which communication phenomena have yet to be explored. Although we may never fully capture the intricacies of the communication process, SEM at least moves us in the direction of understanding a process of interrelated variables more fully and completely.

ACKNOWLEDGMENTS

The authors acknowledge the helpful comments of Nancy Grant Harrington and Teri Thompson in the preparation of this manuscript.

This article is based on a presentation at the Kentucky Conference on Health Communication, "Emerging Trends in Health Communication," Department of Communication, University of Kentucky, April 20–22, 2006, Lexington, Kentucky.

REFERENCES

Ahmed, S., & Mosely, W. H. (2002). Simultaneity in the use of maternal–child health care and contraceptives: Evidence from developing countries. *Demography, 39,* 75–93.

Albrecht, T. L., & Goldsmith, D. J. (2003). Social support, social networks, and health. In T. Thompson, A. M. Dorsey, K. I. Miller, & R. Parrott (Eds.), *Handbook of health communication* (pp. 263–284). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 10,* 411–423.

Austin, E. W., & Chen, Y. J. (2003). The relationship of parental reinforcement of media messages to college students' alcohol-related behaviors. *Journal of Health Communication, 8,* 157–169.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51,* 1173–1182.

Blalock, H. M., Jr. (Ed.). (1971). *Causal models in the social sciences*. Chicago: Aldine.

Bollen, K. A. (1989). *Structural equations with latent variables*. New York: Wiley.

Bollen, K. A. (1996). A limited-information estimator for LISREL models with and without heteroscedastic errors. In G. Marcoulides & R. Schumacker (Eds.), *Advanced structural equation modeling techniques* (pp. 227–241). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Breckler, S. J. (1990). Applications of covariance structure modeling in psychology: Cause for concern? *Psychological Bulletin, 107,* 260–273.

Cacioppo, J. R., Petty, R. E., Feinstein, J. A., & Jarvis, W. B. G. (1996). Dispositional differences in cognitive motivation: The life and times of individuals varying in need for cognition. *Psychological Bulletin, 119, 197–225.*

Cappella, J. N. (1975). Structural equation modeling: An introduction. In P. M. Monge & J. N. Cappella (Eds.), *Multivariate techniques in human communication research* (pp. 57–110). New York: Academic.

Cappella, J. N. (1991). Review of Stephen W. Littlejohn, Theories of human communication (3rd ed.). *Communication Theory, 1,* 165–171.

Chou, C. P., & Bentler, P. M. (1995). Estimates and tests in structural equation modeling. In R. H. Hoyle (Ed.), *Structural equation modeling* (pp. 37–59). Thousand Oaks, CA: Sage.

Cliff, N. (1983). Some cautions concerning the application of causal modeling methods. *Multivariate Behavioral Research, 18,* 115–126.

Crano, W. D., & Burgoon, M. (Eds.) (2002). *Mass media and drug prevention: Classic and contemporary theories and research.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Cudeck, R., du Toit, S., & Sörbom, D. (2001). *Structural equation modeling: Present and future*. Chicago: SSI Scientific Software.

Derzon, J. H., & Lipsey, M. W. (2002). A meta-analysis of the effectiveness of mass-communication for changing substance-use knowledge, attitudes, and behavior. In W. D. Crano & M. Burgoon (Eds.), *Mass media and drug prevention: Classic and contemporary theories and research* (pp. 231–258). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Dillard, J. P., & Peck, E. (2000). Affect and persuasion: Emotional responses to public service announcements. *Communication Research, 27,* 461–495.

Duncan, O. D. (1975). *Introduction to structural equation models*. New York: Academic.

Evans, W. D., Price, S., Blahut, S., Hersey, J., Niederdeppe, J., & Ray, S. (2004). Social imagery, tobacco independence, and the truth campaign. *Journal of Health Communication, 9,* 425–441.

Everett, M. W., & Palmgreen, P. (1995). Influences of sensation seeking, message sensation value, and program context on effectiveness of anticocaine public service announcements. *Health Communication, 7,* 225–248.

Harrington, N. G., Lane, D. R., Donohew, L., & Zimmerman, R. S. (2006). An extension of the activation model of information exposure: The addition of a cognitive variable to a model of attention. *Media Psychology, 8,* 139–164.

Holbert, R. L., & Stephenson, M. T. (2002). Structural equation modeling in the communication sciences, 1995–2000. *Human Communication Research, 28,* 531–551.

Holbert, R. L., & Stephenson, M. T. (2003). The importance of analyzing indirect effects in media effects research: Testing for mediation in structural equation modeling. *Journal of Broadcasting & Electronic Media, 47,* 553–569.

Hornik, R. C. (Ed.). (2002). *Public health communication: Evidence for behavior change.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Hoyle, R. H. (Ed.). (1995). *Structural equation modeling: Concepts, issues, and applications.* Thousand Oaks, CA: Sage.

Hoyle, R. H., & Kenny, D. A. (1999). Sample size, reliability, and tests of statistical mediation. In R. H. Hoyle (Ed.), *Statistical strategies for small sample research* (pp. 195–222). Thousand Oaks, CA: Sage.

Jöreskog, K. G. (1967). Some contributions to maximum likelihood factor analysis. *Psychometrika, 32,* 443–482.

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika, 36,* 183–202.

Jöreskog, K. G. (1973). A general method for estimating a linear structural equation system. In A. S. Goldberger & O. D. Duncan (Eds.), *Structural equation models in the social sciences* (pp. 85–112). New York: Seminar Press.

Jöreskog, K. G., & Lawley, D. N. (1968). New methods in maximum likelihood factor analysis. *British Journal of Mathematical and Statistical Psychology, 21,* 85–96.

Jöreskog, K., Sörbom, D., du Toit, S., & du Toit, M. (1999). *LISREL 8: New statistical features*. Chicago: Scientific Software International.

Kaplan, D. (2000). *Structural equation modeling: Foundations and extensions*. Thousand Oaks, CA: Sage.

Kline, R. B. (1998). *Principles and practice and structural equation modeling*. New York: Guilford.

Lane, D. R., Harrington, N. G., Donohew, L., & Zimmerman, R. S. (in press). Dimensions and validation of a Perceived Message Cognition Value (PMCV) scale. *Communication Research Reports.*

Loehlin, J. C. (1998). *Latent variable models* (3rd edition). Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Lomax, R. (1989). Covariance structure analysis: Extensions and developments. In B. Thompson (Ed.), *Advances in social scientific methodology* (Vol. 1, pp. 171–204). Greenwich, CT: JAI.

MacKinnon, D. P., Lockwood, C. M., Hoffman, J. M., West, S. G., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological Methods, 7,* 83–104.

MacKinnon, D. P., Lockwood, C. M., & Williams, J. (2004). Confidence limits for the indirect effect: Distribution of the product and resampling methods. *Multivariate Behavioral Research, 39,* 99–128.

Maibach, E., & Parrott, R. L. (Eds.). (1995). *Designing health messages.* Thousand Oaks, CA: Sage.

Maruyama, G. M. (1998). *Basics of structural equation modeling.* Thousand Oaks, CA: Sage.

McGuire, W. J. (1986). The myth of massive media impact: Savagings and salvagings. In G. Comstock (Ed.), *Public communication and behavior* (pp. 173–257). New York: Academic.

McPhee, R. D., & Babrow, A. (1987). Causal modeling in communication research: Use, disuse, and misuse. *Communication Monographs, 54,* 344–366.

Miller, M. A., Alberts, J. K., Hecht, M. L., Trost, M. R., & Krizek, R. L. (2000). *Adolescent relationships and drug use.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Mongeau, P. A., & Stiff, J. B. (1993). Specifying causal relationships in the elaboration likelihood model. *Communication Theory, 3,* 65–72.

Mulaik, S. (1972). *The foundations of factor analysis*. New York: McGraw-Hill.

Murray-Johnson, L., Witte, K., Boulay, M., Figueroa, M. E., Storey, D., & Tweedie, I. (2001). Using health education theories to explain behavior change: A cross-country analysis. *International Quarterly of Community Health Education, 20,* 323–345.

Noar, S. M. (2003). The role of structural equation modeling in scale development. *Structural Equation Modeling, 10,* 622–647.

Parrott, R. (2004). Emphasizing "communication" in health communication. *Journal of Communication, 54,* 751–787.

Petty, R. E., & Cacioppo, J. T. (1986). *Communication and persuasion: Central and peripheral routes to attitude change.* New York: Springer/Verlag.

Raykov, T., & Marcoulides, G. A. (2000). A method for comparing completely standardized solutions in multiple groups. *Structural Equation Modeling, 7,* 292–308.

Rice, R. E., & Atkin, C. K. (Eds.). (2001). *Public communication campaigns* (3rd ed.). Thousand Oaks, CA: Sage.

Schmidt, F. L., & Hunter, J. E. (1996). Measurement error in psychological research: Lessons from 26 research scenarios. *Psychological Methods, 1,*199–223.

Schumacker, R. E. (2002). Latent variable interaction modeling. *Structural Equation Modeling, 9,* 40–54.

Schumacker, R. E., & Marcoulides, G. A. (1998). *Interaction and nonlinear effects in structural equation modeling*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Slater, M. D., & Rasinski, K. A. (2005). Media exposure and attention as mediating variables influencing social risk judgments. *Journal of Communication, 55,* 810–827.

Snyder, L. B. (2001). How effective are mediated health campaigns? In R. E. Rice & C. K. Atkin (Eds.), *Public communication campaigns* (3rd ed., pp. 181–190). Thousand Oaks, CA: Sage

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology, 13,* 290–312.

Stephenson, M. T. (2003). Examining adolescents' responses to antimarijuana PSAs. *Human Communication Research, 29,* 343–369.

Stephenson, M. T., Benoit, W. L., & Tschida, D. A. (2001). Testing the mediating role of cognitive responses in the elaboration likelihood model. *Communication Studies, 52,* 324–337.

Stephenson, M. T., & Holbert, R. L. (2003). A Monte Carlo simulation of observable- versus latent-variable structural equation modeling techniques. *Communication Research, 30,* 332–354.

Stephenson, M. T., Hoyle, R. H., Slater, M. D., & Palmgreen, P. (2003). Brief measures of sensation seeking for screening and large-scale surveys. *Drug and Alcohol Dependence, 72,* 279–286.

Stephenson, M. T., & Witte, K. (1998). Fear, threat, and perceptions of efficacy in frightening skin cancer messages. *Public Health Reviews, 26,* 147–174.

Street, R. L., Jr. (2003). Communication in medical encounters: An ecological perspective. In T. Thompson, A. M. Dorsey, K. J. Miller, & R. Parrott (Eds.), *Handbook of health communication* (pp. 63–93. Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Thompson, T., Dorsey, A., Miller, K. I., & Parrott, R. L. (Eds.). (2003). *Handbook of health communication.* Mahwah, NJ: Lawrence Erlbaum Associates, Inc.

Thurstone, L. L. (1947). *Multiple-factor analysis*. Chicago: University of Chicago Press.

Valente, T. W. (2001). Evaluating communication campaigns. In R. E. Rice & C. K. Atkin (Eds.), *Public communication campaigns* (3rd ed., pp. 105–124). Thousand Oaks, CA: Sage.

Witte, K. (1992). Putting the fear back into fear appeals: The extended parallel process model. *Communication Monographs, 59,* 329–349.

Witte, K. (1994). Fear control and danger control: An empirical test of the extended parallel process model. *Communication Monographs, 61,* 113–134.

Witte, K., & Allen, M. (2000). A meta-analysis of fear appeals: Implications for effective public health campaigns. *Health Education & Behavior, 27,* 608–632.

Wright, S. (1934). The method of path coefficients. *Annals of Mathematical Statistics, 5,* 161–215.