Using Structural Equation Modeling (SEM) to Identify, Tease Out, and Quantify a Marketing Program's Influence on Energy Efficiency Intentions and Behaviors

Anne E. Dougherty. Opinion Dynamics Corporation, Oakland, CA
Katherine Van Dusen Randazzo, Ph.D., KVD Research Consulting, San Diego, CA
Pamela Wellner, California Public Utilities Commission, San Francisco, CA

ABSTRACT

Our evaluation team was charged with the difficult task of evaluating the attitudinal and behavioral effects attributable to one of the largest state-funded social marketing campaigns, Flex Your Power (FYP). To complete this evaluation, our team elected to use an innovative statistical technique, structural equation modeling (SEM), to help isolate FYP's effects among a multitude of other influences. This paper will discuss the underlying principles of SEM, and use our research as a teaching example of how this method may be used for other marketing and non-marketing program research and evaluation.

For this evaluation, our key researchable issues were: (1) What are the net effects of FYP on CFL purchase behaviors? (2) What are the indirect effects of the program that help to lead consumers to the purchase of a CFL? (3) What are the program's effects on the CFL behaviors relative to other marketing and outreach programs?

Through our research, we tested which factors had the greatest impact on the purchase of a CFL (such as program messaging, socio-economic status, trust in the messaging, baseline knowledge, location, barriers to purchase, and CFL attributes). The direct and indirect effects on CFL behavior (purchase, installation and storage) were quantified for comparison to gain insight into the relative impact each factor had on the CFL behaviors. From these insights, our team was able to estimate the strengths of various causal paths to behavior change. Thus, we determined FYP's impact on multiple factors leading to behavior change, not simply the behavior change itself.

Introduction

Marketing and outreach efforts (henceforth M&O), unlike traditional resource acquisition programs, pose particular challenges in evaluating the program outcomes and effects. Namely, resource acquisition programs provide a clear link between exposure and action. In addition, their effect on the purchase decision hierarchy through reducing cost is relatively simple to measure and intervenes proximate to the behavioral decision. However, M&O interventions have the potential to generate a series of effects to induce behavior change such as raising awareness, generating knowledge, etc. Thus the methods we use to evaluate the success of these programs must consider, and tease out, multiple influences on the intended behavioral outcome.

Most research efforts that aim to understand multiple influences on consumer purchase behavior have typically used multiple regression techniques to model the processes. These techniques are applied to cross-sectional, quasi-experimental or sometimes longitudinal designs. Whatever statistical technique is used, the goal is to model *causal* processes, teasing out multiple factors that impact the target behavior. The causal forces at work on the consumer are many, complex, and interrelated. Regression approaches make the assumption that the predictors and their errors are uncorrelated, an unrealistic assumption when modeling complex decision-making. These methods also assume that all predictors are measured without error, another unrealistic assumption. Finally, while it is possible to test mediating[1] effects using regression, it is not possible to assess the overall effectiveness of the model being tested when there are indirect effects being modeled which indicates whether the metrics you have included are appropriate for the analysis.

This paper describes a statistical technique and an example of its use that allows more complex processes to be modeled without the assumptions associated with regression. Structural Equation Modeling (SEM) is not new, but has rarely been used in energy efficiency evaluations. SEM allows multiple influences to be teased apart in explaining consumer behavior and account for those influences that are related to one another in complex ways and may not be measurable in isolation.

Background and Scope

The primary focuses of our SEM effort were to: (1) examine customers' motivations for their efficiency behaviors, specifically with CFLs; (2) determine where and how the program messaging may have impacted consumers' motivations through a series of intervening variables; (3) tease out the program effects from other potential influences; and (4) estimate the effect of Flex Your Power (FYP) on *actual CFL behavior*. In addition, we aimed to identify potential sites of optimal intervention to assist in focusing future media campaigns.

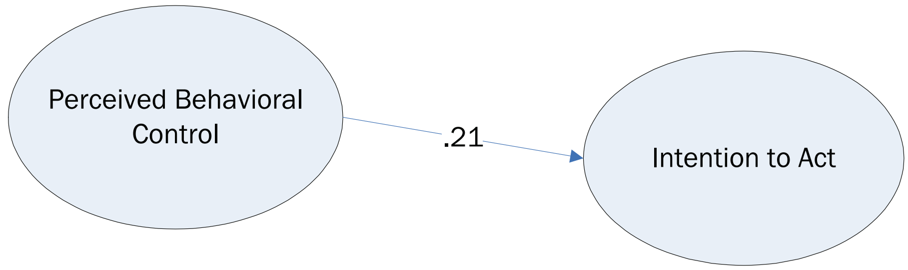
The SEM approach begins with constructing a hypothesized model involving causal relationships between a series of factors we believe may have an effect on the dependent variable. In an SEM model, the effects of one variable on another can be broken down into direct, indirect, and total effects. These effects have meanings similar to path coefficients or standardized regression coefficients. That is, they can vary between -1.00 and +1.00, representing stronger relations as they move toward the ends of that range. Throughout this paper, we discuss only statistically significant path coefficients. While many coefficients in our findings may seem small (e.g. 0.18), they are statistically significant and thus represent a stable and measurable effect. Certain relationships represent greater effects than others. The table below provides a context for the effect sizes you will see throughout the memo.

Table 1. Path Coefficient Range of Effects

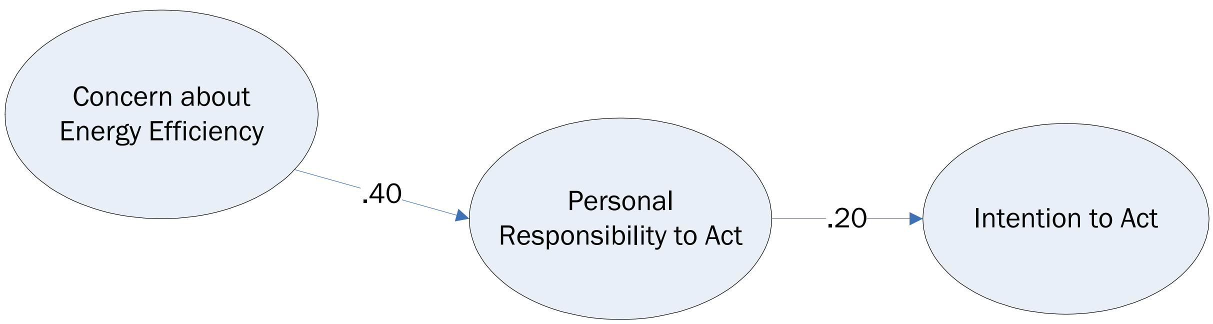
Effect Size	Range of Path Coefficients
Large	.50 or more
Medium	.30
Small	.10 or less

- A variable is said to have a *direct effect* on another variable if it influences that variable directly. In SEM, a direct line connecting one variable to the other indicates that the first variable is having a direct effect on the second variable. In the below diagram, Perceived Behavioral Control has a direct effect of 0.21 on Intention to Act.

[1] A mediator variable is one that attempts to explain the relationship between an independent and dependent variable. Within a model, the direct causal relationship exists between the independent variable and the mediator variable and from the mediator variable and the dependent variable. The relationship between the independent variable and dependent variable is an indirect causal relationship.



- A variable has an *indirect effect* on another variable if it does not directly influence the other variable, but does influence it working through intervening variables. No directed line connects that variable to the variable it has an indirect effect on, but it can reach the variable through following the paths in the model.[2] The value of the indirect effect is determined by multiplying the direct effect by its successor effects going from the path leading from that variable to the other. In the below diagram, Concern about Energy Efficiency has a direct effect of 0.40 on Personal Responsibility to Act and an indirect effect of 0.08 (0.4 * 0.2) on Intention to Act.



Variables may have both a direct and an indirect effect.

- Finally, the *total effect* of one variable on another is the *sum* of all its direct and indirect effects.

Method

Our study focused on the messages broadcast in 2007-2008 by the statewide M&O programs and CFL behaviors made over the prior 12 months using a cross-sectional approach via a one-time survey of customers of the four largest investor-owned utilities in California. Our work included three discrete subtasks: (1) develop models using relevant literature and program theories to ensure that the appropriate concepts were covered, as well as factor analysis to create as parsimonious a survey as possible; (2) conduct focus groups as a way to ensure that our survey instrument was appropriately crafted to engender the same amount of understanding by potential respondents; and (3) create an Internet panel survey effort to collect the data for use for SEM.

We also created hypotheses that the SEM survey was designed to test. This helped us create our original set of constructs. Where possible, we used other literature to help us understand constructs that were found to predict similar types of attitudes and behavior and to design specific question wording around the constructs. This led to our first path model shown in Figure 1..

[2] Schumacker & Lomax, 1996.

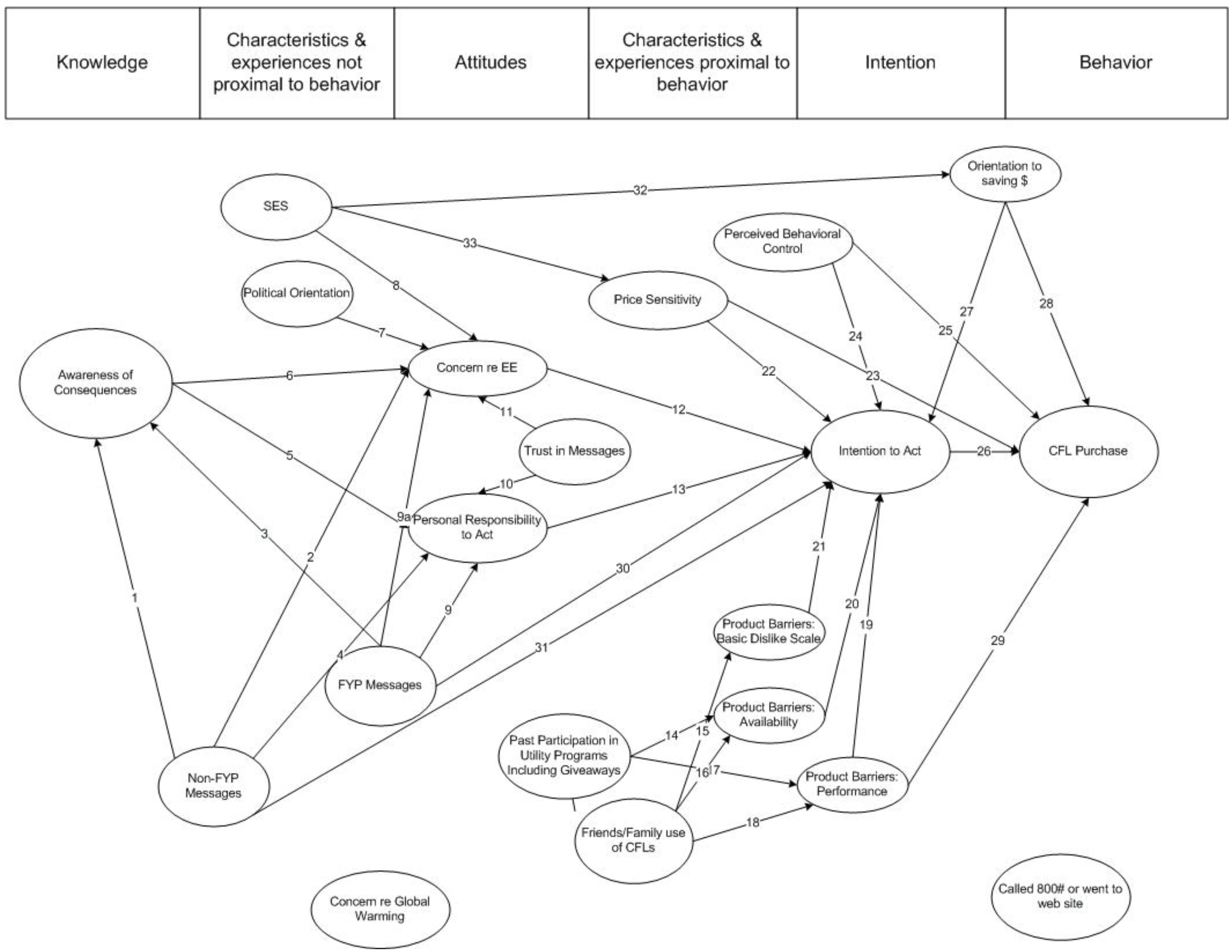


Figure 1. Original CFL Path Model

The Survey

Beginning with this model, we drew on tested survey batteries from the literature[3,4] as much as possible to enhance the rigor of the survey instrument to adequately measure each of the constructs shown in Figure 1. We conducted two pilot studies of 100 respondents each to refine the instrument. The final sample comprised 1,100 completed surveys. In addition to the added level of rigor of two pilot studies, we conducted the survey online specifically to minimize recall bias by showing respondents pictures of the various types of CFLs as well as the media messages the program disseminated.

Our team used the two pilot studies to ensure questions in the survey instrument adequately measured the constructs while reducing redundancy, e.g. to ensure the most rigorous instrument possible while maintaining efficiency in time and budget.

Data Analysis

We analyzed the data using SEM software (EQS) in several steps. Before testing the model, we developed each construct using confirmatory factor analysis (CFA). This involved eliminating items that reduced the fit of the data. We determined the fit of each construct by using Cronbach's alpha, Comparative Fit Index (CFI) and Root Mean Square Error of Approximation (RMSEA). We found that almost all constructs showed at least adequate fit, and those that couldn't be constructed using multiple variable inputs were treated as single variables.

Next, we analyzed the model, as originally hypothesized, but in sections. Each section was built and tested before adding to the core of the model using Intention to Act as the dependent variable. We modified each section as needed, based on what improved or reduced the fit of the model. The program messaging variable was added last as we wanted to first establish the larger processes through which people made their decisions, and then determine how M&O fit into that picture. The table below outlines each construct hypothesized in the original model shown in Figure 1, and also indicates which constructs were retained in the final model.

Table 2. Original Hypothesized Constructs and Number of Survey Indicators[5]

Construct	Original Number of Questions	Final Number of Questions	Constructs Used in Final Model
Price Sensitivity	1 Item	1 Item	
Perceived Behavioral Control	4 Items	1 Item	X

[3] Some survey items could be readily found in the literature, such as personal responsibility-related attitude constructs. However, none of them addressed energy efficiency specifically which was considered important for this study. As necessary, survey questions from the literature were modified and some were eliminated due to redundancy with other questions. In each case, the modifications included inserting energy efficiency content in place of the content specific to the studies they came from.

[4] Bamberg & Schmidt, 2003; Barr, 2007; Berenguer, Corraliza, & Martin, 2005; Black, Stern & Elworth, 1985; Corraliza & Berenguer, 2000; Davies, Foxall, & Pallister, 2002; DeGroot & Steg, 2008; Diekmann & Preisendorfer, 2003; Dietz, Dan, & Shwom 2007; Dietz, Fitzgerald, & Shwom 2005; Dunlap, Van Liere, Mertig, & Jones, 2000); Fishbein and Ajzen 1975; Guagnano, Stern & Dietz, 1995; Hassan, Walsh, Shiu, Hastings, & Harri, 2007; Hunecke, Blobaum, Matthies, & Hoger, 2001; Kaiser, Ranney, Hartig, & Bowler, 1999; Lee & Holden, 1999; Norlund & Garvill, 2002; Oom do Valle, Reis, & Menezes, 2005; Schwartz, 2007; Soonthonsmai, 2001; Stern, Dietz & Kalof, 1993; Stern, Dietz, & Guagnano, 1995; Thogersen, 2002; Wall, Devine-Wright, & Mill, 2007; Weigel & Weigel, 1978

[5] Note: Variables not used in the model were dropped because they didn't add to variance explained in the model.

Product Barrier: Negative View	4 Items	3 Items	X
Product Barrier: Performance	4 Items	4 Items	
Friends & Family Use of CFLs	4 Items	1 Item	X
Concern about Energy Efficiency	8 Items	4 Items	X
Concern about Global Warming	4 Items	3 Items	X
Awareness of Consequences on Environment	3 Items	3 Items	X
Trust in Energy Efficiency Information & Claims	4 Items	4 Items	
Retailer Messaging	3 Items	3 Items	
Orientation to Saving Money-Scale 1	3 Items	3 Items	
Orientation to Saving Money-Scale 2	4 Items	4 Items	
CFL Purchase, Installation, Storage	5 Items	3 Items	X
Intent to Purchase (in Future)	4 Items	3 Items	X
Personal Responsibility to Act	5 Items	5 Items	X
Exposure to FYP	4 Items	3 Items	X
Price Signal	1 Item	1 Item	X
Participation in IOU Programs	Sum of 5 Items to 1 variable	1 Variable	
Exposure to Media Programs on Environmental Issues	Sum of 5 Items to 1 variable		
Exposure to Energy Efficiency Programs (e.g., Energy Star)	Sum of 6 items to 1 variable		
Exposure to Utility Messages	Sum of 5 items to 1 variable	3 Variables	X
Education	1 Item	1 Item	
Income	1 Item	1 Item	
Age	1 Item	1 Item	
Ethnicity	2 Items	2 Items	

A number of constructs in the hypothesized model do not appear in the final model. In general, this is *not* because they are unrelated to Intention to Act or to Behavior. Rather, these constructs were so highly correlated with factors that *are* in the model that they did not add value to this model (in terms of overall fit). The constructs that we excluded were socio-economic status, political orientation, market barriers of availability and performance doubts, trust in global warming and conservation messages, past participation in IOU programs, and orientation to saving money.

Results

Before presenting the detailed results of the analysis, we consider the overall success of the model. This is referred to as "fit" and represents how well the hypothesized model fits our resulting data.[6] We examined three measures of fit as each provides a slightly different perspective on the fit of

[6] In technical terms, the "fit" indicates how well the hypothesized model covariance matrix (a covariance matrix is an unstandardized correlation matrix) corresponds to the observed covariance matrix of all variables with all other variables in the model.

the model.[7] These three measures indicate the model is providing an excellent fit to the data Comparative Fit Index (CFI) = 0.90[8], Chi-square goodness-of-fit probability = 0.26[9], Root Mean Square Error of Approximation (RMSEA) = 0.05[10].

The R^2, or the variance explained by the model, indicates how well the model explains the variance in the dependent variable. The higher the R^2, the better able the model is to explain the dependent variable. For Intention to Act, the primary dependent variable of interest, the variance explained was 63%. We translate this variance into the more commonly used and more general effect size (f^2).[11] The 63% translates to an effect size of 1.7, a very large effect size[12], indicating that the variables with direct effects on the dependent variables are explaining a substantial level of variance in the dependent variable. The variance explained in actual Behavior was 15%. This translates to an f^2 of 0.18, which is larger than what is considered to be a medium effect size (0.15).[13]

The path coefficients (represented by "p" below), as explained earlier, are interpreted like standardized regression coefficients. That is, they can vary between -1.00 and +1.00, representing stronger relations as they move toward the ends of that range. All direct paths shown in the model are statistically significant except the direct path from FYP to CFL Behavior. The latter was left in the model because it is part of a total program effect that is statistically significant.

---

[7] Because the variables were not all normally distributed, it was necessary to use robust measures of fit and statistical tests of significance (Byrne, B., Baron, P., & Campbell, T., 1994).
[8] A value at or above 0.90 is considered a good fit.
[9] This Chi-square value, a measure of the difference between the observed and hypothesized covariance matrix, is not statistically significant. Combined with the large sample size (the Chi-square value tends to be significant for large sample sizes), this indicates that the observed and hypothesized covariance matrices are very similar.
[10] The RMSEA is a measure of the average difference in the correlations between observed and hypothesized matrices, after adjusting for the size of the correlations. Although what is considered a bad and a good RMSEA varies by author, a common interpretation is that at or below 0.15 is adequate and at or below 0.08 is good.
[11] The f^2 is defined as the explained variance divided by the unexplained variance. For example, for an R^2 of 63%, the f^2 is calculated as: 0.63/0.37 = 1.7.
[12] According to Cohen, 1988 a standard large effect size (in f^2 terms) is considered to be 0.35.
[13] Cohen, 1988.

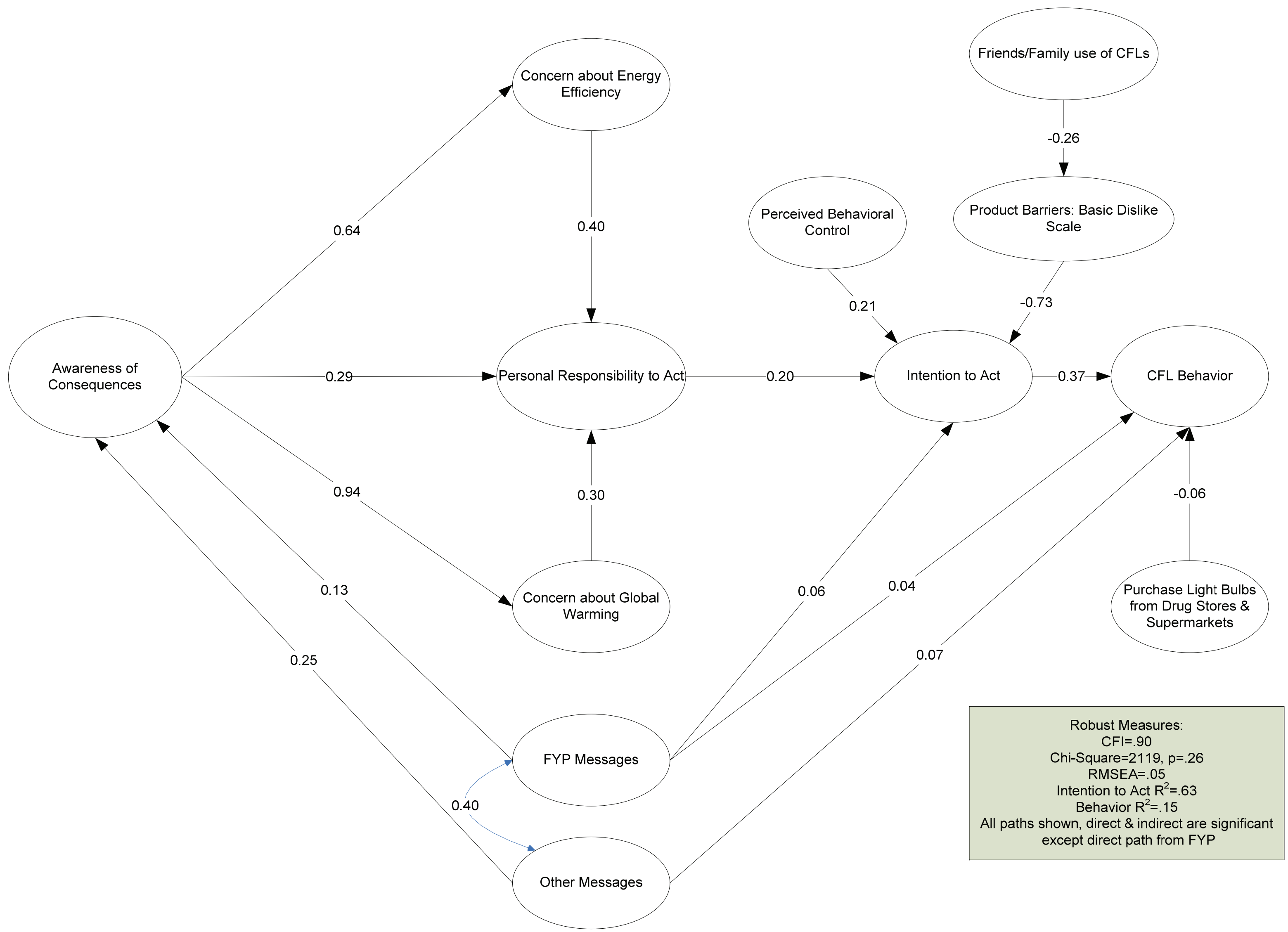


Figure 2. SEM Model Predicting: Intention to Act and CFL Behavior

Knowledge and Attitudes

The four ovals on the upper left side of the model in Figure 2 represent the cluster of attitude factors that we hypothesized would play an important role in moving consumers from exposure to the program's messaging to Intention to Act. Our findings indicate that Personal Responsibility to Act is the central attitudinal factor, in that all other attitude and knowledge factors feed into it. Through our analysis of attitudes, we found the strongest predictor of taking Personal Responsibility for Action is Concern about Energy Efficiency (p=.40), followed by Concern about Global Warming (p=.30). The most likely reason why energy efficiency is a bit more important than global warming in this model is that the focus of the model is on CFLs, a measure specific to energy efficiency. Awareness of Consequences is essentially equivalent to Concern about Global Warming in its impact on Personal Responsibility for Action (p=.28 versus p=.30), but we found that it is a powerful predictor of both Concern with Global Warming (p=.94) and Concern with Energy Efficiency (p=.64).

In addition, we found that the connection between Awareness of Consequences and the "concern" factors is so strong (p=.94 and p=.64 respectively), that we questioned whether we were measuring the same concern, which would mean that Awareness of Consequences could be removed from the model. We tried removing Awareness of Consequences from the model, but this significantly reduced the fit of the model. Thus, we concluded that Awareness of Consequences is an important intervening variable in the decision to take energy efficiency actions.

Predictors of CFL Purchase Intention

Using our model, we found that the greatest predictors of one's Intention to Act are from specific product barriers related to the overall dislike of CFLs. As a group, these are very strong negative predictors of intention (p= -.74). We also measured other barriers in the model, but these were statistically less significant than respondents' general dislike of CFLs, which was represented by the Dislike CFLs construct. Thus, we removed these barriers from the model as they didn't contribute enough beyond the Dislike construct. We also found that the general dislike barrier is influenced (in a negative direction) by the level of CFL usage by Friends & Family (p= -.26), indicating that social influences have an indirect influence on Intention to Act, indicating that, when influenced through a negative product perception, have the effect of offsetting negative product barriers.

In addition, we measured another social influence: the concept of Perceived Behavioral Control. We determined that this construct, in particular, was an important one from the literature predicting "green" behaviors. For our model, Perceived Behavioral Control measured the degree to which the actor feels s/he has the ability to act without interference from someone else (e.g., family members). It is a moderate predictor of Intention to Act (p=.21) in this study.

Program Effects

Once the core model estimating Intention to Act was completed, we added variables for FYP messaging and non-FYP messaging to assess the program's effects through: (1) its indirect effect through the core constructs (knowledge and attitudes); and (2) its direct effects on intention to act and CFL behaviors. We hypothesized that the M&O interventions would affect Intention to Act mainly through Awareness of Consequences and the paths that flow from there through the rest of the model. In other words, we hypothesized that the ads and programming provided powerful messages about the consequences of global warming and how it can be affected by reducing energy usage, and thus the program's primary path of influence would be through attitudes. However, we did also measure the direct effects of the program's messaging, as it is possible that the advertising may have an influence on CFL purchase intent and behavior without influencing the intervening variables.

In terms of indirect effects, we found that the program messaging and similar non-program messaging have a moderate impact on Awareness of Consequences (p=.13 and p=.25, respectively). It seems that the messaging has its impact on the attitude factors through its impact on Awareness of Consequences rather than directly on the "concern" factors of global warming and energy efficiency as there were no direct effects of M&O on other attitudinal constructs.

The effects of M&O, both direct and indirect, on Intention to Act are small but statistically stable. The total effect[14] of the program on Intention to Act is small, with a path value of .08. The total effect of non-program messages is .04, so the total effect of all messaging comes to .12.

Similarly, we found that the effects of M&O on CFL behavior were small but stable. [15] The total effect of program messaging on CFL Behavior is .07, and the total non-FYP effect is .08, for a total messaging effect of .15.

Summary and Conclusions

Summary

Our SEM model addresses both the direct and indirect effects of the Flex Your Power Program Marketing & Outreach on two constructs: (1) Intention to Act; and (2) CFL Behavior. We found that the strongest impact of the program is indirect, through its influence on participants' Awareness of Consequences. This awareness then seems to have an impact on a series of attitudinal shifts, namely Concern about Energy Efficiency, Concern about Global Warming, and Personal Responsibility. This resulting sense of Personal Responsibility then leads to Intention to Act and then to Behavior. Our research also found that the program's M&O and other similar non-FYP messaging do have direct effects on Intention and Behavior, although these effects are small.

Conclusions

Structural Equation Modeling provides policymakers and program implementers with a robust and in-depth analysis of a series of influences on a behavioral outcome. In addition, SEM provides the unique ability to model both direct and indirect effects, to allow predictors to be correlated, and to portray the larger picture of influences on consumer intentions and behavior. Each of these benefits of SEM helps provide valuable process and impact evaluation insights. Namely, SEM allows policymakers to measure the overall effects of M&O on behavior while also laying clear where M&O might have the greatest effect on the behavioral outcome for future interventions.

We found that the current program's impact on Intention and Behavior is small, but statistically significant. With this finding, we are better able to provide a context for the effects of the M&O that we measure through more traditional survey analysis techniques, while also gaining knowledge on how and where the program may be having its greatest impact along the behavior change continuum.

Additionally, SEM was able to show that the strongest predictor of Intention is the level of general dislike of CFLs, which provides insight on a promising secondary marketing message for

[14] The total effect is the sum of the direct and indirect (i.e., acting through intervening attitude variables) effects.

[15] It is important to note here that we measured the correlation between Exposure to FYP and Other Messaging. This was an important part of estimating the SEM model. We found the two are strongly correlated at r=.40. By allowing this correlation, which would be impossible in standard regression modeling, our SEM analysis permits the non-shared variance in these two measures to be partitioned from the shared portion, and to have separate relations with other variables in the model.

influencing consumers: addressing the reasons that they dislike CFLs. The program could also focus on the product itself and the consumers' perception of it to intervene more proximally to the consumers' intention to act.

Caveats and Benefits

One can argue that concern for the environment, global warming, or energy efficiency might cause the customer to become aware of the consequences of not conserving energy rather than the other way around (as we portray it in the model). There is likely some truth in this argument, but knowledge generally and logically precedes attitudes, which is why we modeled it this way. However, reverse causality is probably present in some degree on a number of model paths.

The policymaker must consider the fact that FYP and other programs with similar goals have been in field for years, so we cannot expect the incremental program effects to be large for this single evaluation year. In the early stages of acceptance of a technology such as CFLs, we would include a number of knowledge and awareness constructs for predicting intention to purchase, and we would expect the program to impact them. However, the California population is now beyond this stage. Some of the effect of the early program years and the upstream lighting programs will have contributed to a baseline acceptance that this program cycle and this study have built upon. Thus, it is impossible to capture the entire effect of the program using any method, as no data was collected in the early stages of the program, which is required to model the change over time.

Furthermore, one of the challenges of this study has been that such a large number/percentage of California residents are already "sold" on the idea of CFLs. This makes the distribution of the answers to many of our survey questions highly skewed; for example, sometimes as many as 60% of the respondents chose the most extreme response category to attitude and behavior questions. This is difficult both methodologically and substantively, as noted above, as so much of the change in acceptance has already happened.

Still, the problems mentioned here are not unique to this method of analysis and are indeed common across most methods currently used to assess program impacts. The SEM method reduces some problems that evaluators consistently face and provides opportunities to see a more multifaceted picture which, in turn, allows policymakers to make more informed decisions. The method and the study's large sample size allow us to see small and statistically significant effects. Even a small program effect can have large consequences when applied to a large population.

References

Bamberg, S., & P. Schmidt 2003. "Incentives, morality, or habit? Predicting students' care use for university routes with the models of Ajzen, Schwartz, and Triandis." *Environment and Behavior, 35,* March: 264-285.

Barr, S. 2007. "Factors influencing environmental attitudes and behaviors." *Environment and Behavior, 39,* July: 435-473.

Berenguer, J., J.A. Corraliza, & R. Martin 2005. "Rural-urban differences in environmental concern, attitudes and actions." *European Journal of Psychological Assessment*, *21*, April: 128-138.

Black, J.S., P.C. Stern, & J.T. Elworth 1985. "Personal and contextual influences on household energy adaptations." *Journal of Applied Psychology, 70,* February: 3-21.

CBEE 1999. *CBEE Baseline Study On Public Awareness And Attitudes Toward Energy Efficiency: Final Report. California Board for Energy Efficiency*.

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences* 2nd ed. Hillsdale, NJ: Lawrence Erlbaum.

Corraliza, J.A. & J. Berenguer 2000. "Environmental values, beliefs and actions: A situational approach." *Environment and Behavior, 32,* November: 832-848.

Davies, J., G.R. Foxall, & J. Pallister 2002. "Beyond the intention-behaviour mythology: An integrated model of recycling." *Marketing Theor*y*, 2,* March: 29-113.

De Groot, J.I.M., & L. Steg 2008. "Value orientations to explain beliefs related to environmental significant behavior: How to measure egoistic, altruistic, and biospheric value orientations." *Environment and Behavior, 40,* May: 330-354.

Diekmann, A. & P. Preisendorfer 2003. "Green and Greenback: The behavioral effects of environmental attitudes in low-cost and high-cost situations." *Rationality and Society, 15,* November: 441-472.

Dietz, T., A. Fitzgerald, & R. Shwom 2005. "Environmental values." *Annual Review of Environment and Resources, 30,* November: 335-72.

Dietz, T., A. Dan, & R. Shwom 2007. "Support for climate change policy: Social psychological and social structural influences." *Rural Sociology, 72*, June: 185-214.

Dunlap, R.E., K.D. Van Liere, A.G. Mertig, & R.E. Jones 2000. "Measuring endorsement of the new ecological paradigm: A revised NEP scale." *Journal of Social Issues, 56*, September: 425-42.

Fishbein, M., & I. Ajzen 1977. *Belief, attitude, intention and behavior: An introduction to theory and research.* Reading, MA: Addison-Wesley.

Guagnano, G.A., P.C. Stern, & T. Dietz 1995. "Influences on attitude-behavior relationships: A natural experiment with curbside recycling." *Environment and Behavior, 27*, September: 699-718.

Hassan, L.M., G. Walsh, E.M.K. Shiu, G. Hastings, & F. Harri, 2007. "Modeling persuasion in social advertising: A study of responsible thinking in antismoking promotion in eight eastern EU (European Union) member states." *Journal of advertising, 36*, March: 15-31.

Hunecke, M., A. Blobaum, E. Matthies, & R. Hoger,2001. "Responsibility and environment: Ecological norm orientation and external factors in the domain of travel mode choice behavior." *Environment and Behavior, 33*, November: 830-852.

Kaiser, F.G., M. Ranney, T. Hartig, & P.A. Bowler 1999. "Ecological behavior, environmental attitude, and feelings of responsibility for the environment." *European Psychologist, 4,* June: 59-74.

Lee, J.A. & S.J.S. Holden 1999. "Understanding determinants of environmentally conscious behavior." *Psychology and Marketing, 16,* August: 373-392.

Norlund, A.M. & J. Garvill 2002. "Value structures behind proenvironmental behavior." *Environment and Behavior, 34*, November: 740-765.

Oom Do Valle, P., E. Rebelo, E. Reis, & J. Menezes.2005. "Combining behavioral theories to predict recycling involvement." *Environment and Behavior, 37*, May: 364-396.

Schwartz, N. 2007. "Attitude construction: Evaluation in context." *Social Cognition, 25*, September: 638-656.

Soonthonsmai, V. 2001. *Predicting intention and behavior to purchase environmentally sound or green products among Thai consumers: An application of the theory of reasoned action*. UMI No. 9315947.

Stern, P.C., T. Dietz, & G.A. Guagnano 1995. "The new ecological paradigm in social-psychological context." *Environment and Behavior, 27*, November: 723-743.

Stern, P.C., T. Dietz & L. Kalof 1993. "Value orientations, gender, and environmental concern." *Environment and Behavior, 25*, September: 322-348.

Thogersen, J. 2002. "Direct experience and the strength of the personal norm-behavior relationship." *Psychology & Marketing, 19*, October: 881-893.

Wall, R., P. Devine-Wright & G.A. Mill 2007. "Comparing and combining theories to explain proenvironmental intentions: The case of commuting-mode choice." *Environment and Behavior, 39*, November: 731-753.

Weigel, R. & J. Weigel 1978. "Environmental concern: The development of a measure." *Environment and Behavior, 10*, March: 3-15.