Running head: TOP-DOWN AND BOTTOM-UP MODELS

# Top-Down and Bottom-Up Models of Life Satisfaction Judgments

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An important goal of survey research is to identify characteristics that foster high quality of life. Presumably, this goal can be attained by assessing life circumstances and examining their effect on life satisfaction judgments. This approach assumes that people construct life satisfaction judgments in a “bottom-up” manner by first assessing the conditions in their lives and then aggregating across conditions to arrive at an overall evaluation. An alternative model posits that judgments are formed through a “top-down” process in which people first compute a general life satisfaction judgment and then rely on this general feeling when judging more specific domains. If the top-down model is correct, then self-report measures of satisfaction (particularly domain satisfaction) should provide little insight into the factors that are responsible for high quality of life. Previous research on the top-down/bottom-up controversy has been limited by its reliance on quantitative models with restrictive and potentially inappropriate assumptions. However, the multi-wave nature of the GSOEP dataset is uniquely suited to addressing this questions about these effects. The current paper uses latent state-trait models to decompose the variance in satisfaction measures into theoretically meaningful components. Results suggest that bottom-up processes contribute substantial amounts of variance to satisfaction measures, and that top-down effects result from both dispositional and occasion-specific effects.

Top-Down and Bottom-Up Models of Life Satisfaction Judgments

All sciences strive to improve people's lives. The health sciences, for instance, attempt to identify the factors that promote physical health and well-being. The social sciences hope to clarify which economic, societal, and psychological factors lead to better lives for individuals. Even the natural sciences search for ways to make life better through new inventions or new insights into the way that the physical world affects human life. In each of these disciplines, the immediate goal of the science—whether it be freedom from disease, thriving economies, or healthy environments—is useful insofar as it increases general feelings of subjective well-being (SWB) among the population. A medical treatment that extends life may not be considered a success if its side effects make people miserable. A government's economic policies may be seen as a failure if their implementation leads to a decrease in the population's life satisfaction. Feelings of happiness and life satisfaction can be seen as an ultimate outcome towards which all sciences strive.

Thus, it is no surprise that measures of life satisfaction and happiness are often included in large-scale national surveys. Diener and Seligman (in press) even argued that governments should implement systematic and standardized procedures for measuring and tracking national levels of well-being over time. They suggested that such measures could inform policy decisions at the national level. When judging the success of particular policies, effects on SWB could be examined. Universal health care may increase the physical well-being of a population, but the economic costs of the policy may lead to less satisfaction in other life domains. By tracking levels of happiness, costs in one domain and benefits in another can be compared on a common metric.

Proposals about the implementation of national measures of well-being rest on certain assumptions about how well-being judgments are made. Specifically, if these judgments are to be useful in guiding public policy, then they must be reactive to changing life circumstances. Respondents should systematically evaluate the conditions in their lives and use this information to create satisfaction judgments. If an important life domain changes, then the life satisfaction judgment should reflect that change. In other words, for well-being judgments to be useful in guiding public policy, they must be created—at least in part—in a bottom-up fashion.

Yet researchers know that satisfaction judgments are not created in a purely bottom-up manner. Even the earliest well-being theorists acknowledged that objective circumstances will not always influence global satisfaction judgments. Campbell, Converse, and Rodgers (1976), for instance, posited that there are a number of steps that must occur before a satisfaction judgment can be made. Once individuals perceive an objective condition within a particular domain (e.g., the amount of money they have), they must compare that condition to a variety of standards to determine where they stand on that domain (see Michalos, 1985, for a more detailed model of comparison standards). For instance, people may compare the amount of income they currently have to the amount they have had in the past, the amount they expect to have in the future, or the amount that their neighbors have. Respondents then use that information to create a domain satisfaction rating. However, because domains vary in importance across individuals, respondents must also weight each domain for importance before using that information to create an overall judgment. According to Campbell et al., it is the weighted average of these domain satisfaction judgments that leads to overall life satisfaction judgments. The fact that domain satisfaction ratings often correlate moderately to strongly with life satisfaction ratings provides initial support for this type of bottom-up model (Schimmack, Diener, & Oishi, 2002).

However, in the time since Campbell et al. (1976) formulated their model, various empirical findings have led to questions about the extent to which judgments are created in a bottom-up manner. For instance, research shows that the objective life circumstances that should, theoretically, form the basis for life satisfaction judgments do not play a strong role in determining global well-being judgments (Diener, Suh, Lucas, & Smith, 1999). Even the most optimistic proponents of the role of life circumstances have suggested that these external variables can account for, at most, 15-20% of the variance in global satisfaction judgments (Argyle, 1999). In addition, well-being judgments are stable over time, even when objective life circumstances change (Costa, McCrae, & Zonderman, 1987; Costa, Zonderman, McCrae, Cornoni-Huntley, Locke, & Barbano, 1987; Lucas, Diener, & Suh, 1996; Watson & Walker, 1996). Furthermore, satisfaction reports are moderately to strongly associated with stable personality traits and they have a moderate to strong genetic component (see Diener & Lucas, 1999, for a review). Lykken and Tellegen (1996), for instance, showed that 80% of the long-term stable variance in well-being judgments could be explained by genetic factors. Together, these findings have led some researchers to conclude that global well-being measures are not influenced by objective life circumstances and are instead determined by stable personality traits.

These dispositional theories of well-being judgments further posit that the association between reports of domain satisfaction and global life satisfaction does not result from the bottom-up influence of domains on global satisfaction. Instead, these theorists argue, the causal arrow goes in the opposite direction. According to *top-down models of well-being*, various dispositional factors influence global judgments of life satisfaction. These global judgments, in turn, influence perceptions of and satisfaction with various life domains. For instance, happy individuals may attend only to the positive aspects of a particular life domain (Diener, Lucas, Suh, & Oishi, 2002). Or, when making a satisfaction judgment, they may not even systematically examine the conditions in life, instead relying upon current mood and global judgments as quick heuristic-based proxy judgments for domain satisfaction. According to this perspective, a happy person will be satisfied with the domains in his or her life, regardless of his or her objective standing in those domains. If satisfaction judgments were created in this way, then changes in external conditions should have little effect on domain or life satisfaction ratings, and public policy initiatives could not be evaluated by examining their effects on well-being.

## The Nature of Top-Down Effects

Although the possibility that global satisfaction can influence domain satisfaction is often acknowledged by researchers, strong theories about the nature of this effect are often not articulated. Yet top-down effects can occur for a variety of reasons, and these different processes may have different implications for theories and measures of well-being. Most researchers who investigate top-down effects attribute these effects to unspecified dispositional processes that affect the covariance between *reports* of domain and life satisfaction. It is presumed that happy people will report being satisfied with all domains of their lives, even if these domains are objectively bad. Clearly, such effects would pose problems for researchers interested in using reports of well-being to guide public policy.

Yet, some types of top-down effects are less problematic. For instance, Headey and Wearing (1991) suggested that top-down effects may occur because happy people actually have more good things happen to them. They used a panel study to show that subjective happiness reports prospectively predicted the occurrence of future events. A number of other researchers have replicated these findings with such important outcomes as mortality (Danner, Snowdon, & Friesen, 2001), marriage (Lucas, Clark, Georgellis, & Diener, 2003), unemployment (Diener, Nickerson, Lucas, & Sandvik, 2002; Lucas, Clark, Georgellis, & Diener, 2004) and income (Diener, Nickerson, et al., 2002; Marks & Fleming, 1999). Thus, happiness may actually cause the objective conditions on which domain satisfactions are based. This type of top-down effect does not pose a problem for survey researchers because it does not rule out the possibility that public policy decisions and other interventions can influence domain and life satisfaction.

In addition, it is possible that some top-down effects do not occur through dispositional processes at all. For instance, Schwarz and Strack (1999) suggested that individuals rarely conduct an exhaustive search of their memories when creating satisfaction judgments. Instead, they often rely on heuristics to make such judgments. For example, when making satisfaction judgments, respondents may simply rely on their current mood (e.g., Schwarz & Clore, 1983). If current mood affects domain and life satisfaction measures in similar ways, then top-down effects would emerge. However, these top-down effects may not be stable across different occasions, and they would not be the result of dispositional processes. Existing research on top-down and bottom-up models rarely, if ever, empirically separates the various types of top-down effects. Because each type of effect has implications for the validity of well-being measures (and for theories of well-being), such specificity is needed.

## Testing Top-Down and Bottom-Up Models

For both practical and ethical reasons, it is difficult to experimentally manipulate domain or global satisfaction. As a result, a variety of correlational research techniques have been developed to tease apart top-down from bottom-up effects. Unfortunately, many of these techniques rely on questionable assumptions about the nature of well-being. For instance, one of the most commonly used designs is the cross-lagged panel design (e.g., Feist, Bodner, Jacobs, Miles, & Tan, 1995; Judge & Watanabe, 1993; Brief, Butcher, George, & Link, 1993; Saris, 2001; Schyns, 2001). In this design, life satisfaction and domain satisfaction are measured on at least two occasions. The cross-lagged effect of initial life satisfaction on later domain satisfaction is examined to assess top-down effects, and the effect of initial domain satisfaction on later life satisfaction is examined to assess bottom-up effects. If life satisfaction is associated with domain satisfaction at a later point in time, then this is consistent with the idea that life satisfaction has a causal role in the relation (though of course, this does not prove causality).

Although the logic of the cross-lagged design is clear, the value of this design depends on the time course of the processes being investigated (Headey, Veenhoven, & Wearing, 1991). Cross-lagged designs are not useful when effects are instantaneous, as both top-down and bottom-up processes are likely to be. There is no reason to expect a change in satisfaction with one's health, for instance, to have a lagged effect on one's satisfaction with his or her life. Instead, this effect should occur instantaneously. Similarly, if global satisfaction judgments are used as a quick heuristic when rating domains (a top-down effect), then simultaneous correlations between the two constructs should account for the association. Although cross-lagged effects have been found in many studies, it is questionable whether these effects would be predicted from either top-down or bottom-up theories. Thus, cross-lagged panel designs are limited in their ability to address questions regarding underlying processes.

A second type of design that has been used to address these questions involves the use of non-recursive structural equation models. In most regression-based analyses, one can estimate the effect of domain satisfaction on life satisfaction or the effect of life satisfaction on domain satisfaction, but not both of these effects simultaneously. In non-recursive models, however, both types of effects can be modeled. One way to estimate such models is to include instrumental variables in the model (e.g., Judge & Watanabe, 1993; Mallard, Lance, & Michalos, 1997; Schyns, 2001). According to Mallard et al., instrumental variables are those that have a direct and non-reciprocal effect on only one of the two variables of interest. For instance, if a researcher was trying to estimate the associations between income satisfaction and life satisfaction, he or she may include actual income as an instrumental variable that should be directly and causally related to income satisfaction but only indirectly related (through income satisfaction) to life satisfaction. By including instrumental variables for each of the two variables in a reciprocal relation, the independent effects of each variable on the other can be estimated.

Unfortunately, variables that meet the necessary criteria are difficult to find in the area of SWB. For instance, Mallard et al. used the discrepancy between what an individual has and what he or she wants as instrumental variables that should theoretically be related only to domain satisfactions. However, Lyubomirsky and her colleagues have shown that happiness affects a variety of cognitive processes related to desires (see Abbe, Tkach, & Lyubormirsky, 2003, for a review). For instance, unhappy people are likely to denigrate options that have been foreclosed, whereas happy people are not. Thus, it is possible that have-want discrepancies result from life satisfaction judgments and therefore do not provide appropriate instrumental variables with which to assess reciprocal relations. Other researchers have examined the association between job satisfaction and life satisfaction by including various exogenous job characteristics (salary, prestige, hours worked, etc.) as instrumental variables (e.g., Judge & Watanabe, 1993). However, Lucas and Diener (2003) reviewed evidence that well-being may influence a variety of such work-related outcomes. Thus, it is questionable whether any appropriate instrumental variables can be found. If the specific instrumental variables are not appropriate, then estimates of top-down and bottom-up effects will not be correct. In support of this suggestion, Sherpenzeel and Saris (1996) found that estimates from this type of model are not stable and do not replicate well across studies.

A second way to estimate non-recursive models is to use multiple waves of data and to impose constraints that allow for model identification (e.g., Headey et al., 1991). For instance, Headey et al. used four waves of panel data to estimate the top-down and bottom-up associations between domain and life satisfaction. To identify the model, the year-to-year stability of life and domain satisfaction, certain residual variances, and the top-down, bottom-up, and non-directional same-wave associations had to be constrained to equality across all four waves. Although one could make the case that such constraints are theoretically justifiable (as one would expect the constructs to relate to one another in similar ways across years), a model with such constraints may not fit the data.

To demonstrate, I tested these assumptions in Headey et al.'s data using a much simpler model in which each wave of life and domain satisfaction was predicted only from the same construct at the previous wave. I also allowed the residual variance for life satisfaction at one wave to be correlated with the residual variance for marital satisfaction at the same wave. The estimated cross-wave stability of life satisfaction was fairly consistent across all three waves (.78, .74, and .80), but the stability of marital satisfaction increased steadily over time (.56, .72, and .80). As a result, the covariance between the residual variance at each wave steadily decreased over time from .67 at Wave 2 to .36 at Wave 4. Constraining the stabilities and covariances to be equal across waves led to a significant decrease in fit, $\chi^2$ (6, $N$ = 350) = 39.87,

$p < .001$. Misspecification in one part of the model could lead to incorrect estimates in other parts of the model, including in the top-down and bottom-up parameters of interest.

A final method that has been used to investigate top-down versus bottom-up effects is to measure both life and domain satisfaction, and then to see whether the constructs still relate to one another even after controlling for a variety of theoretically relevant personality characteristics. For instance, Heller, Judge, and Watson (2002) measured job satisfaction and life satisfaction and then controlled for variables such as neuroticism, extraversion, conscientiousness, positive affect, negative affect, self-esteem, self-efficacy, and locus of control. They found that the correlation between life and domain satisfaction was reduced when various personality characteristics were controlled, though their claim that "the relationships disappears once the confounding role of core self-evaluations is taken into account" (p. 829) was not completely supported by their data. The correlation was still significant when these personality characteristics were included (see footnote 4 on p. 829). Thus, there is more to the association than personality traits alone. In addition, simply controlling for measures of personality traits cannot determine whether the causal arrow runs from personality to the satisfaction dimensions.

Ultimately, questions about the causal direction of the association between life and domain satisfactions may be unanswerable. Cross-lagged designs cannot solve the problem because the effects may be instantaneous. Nonrecursive models may rely on too many untenable and restrictive assumptions. And studies that covary out the effects of personality traits simply identify the amount of variance that is shared among various constructs; these studies cannot determine which factors have causal priority. Furthermore, results from studies using these designs have been somewhat inconsistent, and neither top-down nor bottom-up effects appear to be strong enough to account for the associations between domain and life satisfactions. For instance, my reanalysis of Headey et al.'s data showed that correlations between latent marital satisfaction and latent life satisfaction were around .64, meaning that about 41% of the variance in life satisfaction could be explained by domain satisfaction (and vice versa). Yet, the estimated top-down effect was just .12 (meaning that life satisfaction explained just 1% of the variance in marital satisfaction) and the bottom-up effect was just .18 (meaning that marital satisfaction explained just 3% of the variance in life satisfaction). Although many studies have been conducted using these techniques, no clear conclusions about the relative contribution of top-down versus bottom-up effects have emerged.

## New Methods for Estimating Top-Down and Bottom-Up Effects

Existing studies of top-down and bottom-up models focus on the covariance between satisfaction with a single domain and satisfaction with life. These studies attempt to decompose this covariance into directional top-down and bottom-up effects. As noted above, the techniques for decomposing the covariance in this way are problematic, and no clear consensus about the relative contribution of top-down versus bottom-up effects has been reached. Yet, top-down and bottom-up models do not just differ in their predictions about directional effects. Thus, alternative techniques for investigating these processes may provide more concrete answers.

For instance, both top-down and bottom-up models suggest that domain satisfaction measures should be moderately to strongly correlated with life satisfaction, but these models differ in their predictions about how strongly domain satisfaction measures should correlate with one another. Bottom-up models predict that domain satisfaction measures should correlate only to the extent that the objective factors within these domains correlate. Top-down models, on the other hand, suggest that various domain satisfaction ratings should be strongly correlated because each of these ratings is infused with top-down variance. Therefore, top-down models predict that various domain satisfaction measures should cohere strongly enough to form a single higher-order factor, and that this higher-order factor should contribute substantial amounts of variance to the lower-order domain satisfaction measures.

Furthermore, the amount of variance that can be accounted for by this higher-order factor provides an upper-bound estimate of the impact of top-down effects. This shared variance may overestimate top-down effects because covariance in the objective conditions that lead to domain satisfactions would also lead to a higher-order factor. However, these covariances are likely to be small, and much of the variance in such a higher-order factor could be considered top-down variance. No study has decomposed the variance in domain satisfaction measures in such a way to allow for tests of these predictions. By decomposing the variance in domain satisfaction measures, novel predictions can be tested.

In addition, disposition-based top-down theories predict that variance that is shared among domain satisfaction measures should be stable over time. Yet it is possible that the variance that is shared among concurrent domain satisfaction measures results from current mood (or other occasion-specific) effects. Again, no study has determined the extent to which various types of top-down effects are responsible for the covariation among domain satisfaction measures and between domain and life satisfaction measures. Such specificity is necessary before underlying processes can be identified.

One reason that these questions have not been answered is that to do so, complicated analytic models are required. In addition, these models are often data intensive. However, recent developments in structural equation modeling techniques (combined with multi-wave panel studies) allow for novel tests of predictions from top-down and bottom-up models.

Specifically, models based on latent state-trait theory (LST; Schermelleh-Engel, Keith, Moosbrugger, & Hodapp, 2004; Steyer, Schmitt, & Eid, 1999) allow variance in a measure to be decomposed into distinct components. For instance, if multiple traits are measured over multiple occasions, variance can be decomposed into latent trait variance, latent occasion variance, and residual variance that is unexplained by the other three components. When multiple traits are used, more complicated hierarchical latent state-trait models can determine the extent to which latent trait variance is attributable to a higher-order latent factor (Schermelleh-Engel et al.)

Schermelleh-Engel et al. (2004) used hierarchical LST models to examine the nature of test anxiety. In their model, four components—emotionality, interference, worry, and lack of confidence—were measured on three occasions, each time using three different questions per trait. The researchers were then able to determine whether there was a general test anxiety factor, whether this factor explained substantial portions of the variance in each lower-order latent trait, and whether specific question and occasion factors added variance to the observed measures. Estimates can be compared to predictions from various models to determine the extent to which the data support one model over the other.

If top-down models of life satisfaction are correct, domain satisfaction measures should cohere strongly enough to form a single higher-order factor. This factor should account for much of the variance in domain satisfaction measures. In addition, if this factor results from stable personality dispositions, occasion-specific factors should contribute very little to the covariance among domain satisfaction measures. Finally, by including exogenous variables in the model, it is possible to determine the extent to which shared or unique trait variance is associated with external factors. For instance, by including objective measures of health in the model one can determine whether domain satisfactions are directly associated with objective factors. If objective measures of health are directly related to the unique variance in health satisfaction, then this suggests that strong bottom-up processes are at work. In addition, if objective health is associated with the general satisfaction factor, then this suggests that general satisfaction is not simply a measure of unwanted dispositional effects. Instead, associations between the general factor and exogenous factors would reflect the true influence of bottom-up processes on the shared variance linking domain satisfaction ratings.

## Summary

The goal of this paper is to use hierarchical LST models (Schermelleh-Engel et al., 2004) to determine the extent to which measures of domain and life satisfaction reflect (a) stable levels of global satisfaction, (b) stable levels of unique, domain-specific variance, (c) occasion-specific global satisfaction, and (d) residual variance that cannot be explained by either of the other three factors. In addition, by including exogenous variables such as health status and income levels, questions about the nature of the higher-order global factor can be answered. If these exogenous variables correlate with the higher-order factor than this factor is not simply unwanted (and invalid) top-down variance. Instead, it reflects valid covariance among the objective conditions in a person's life. Together, the models will allow for precise tests of top-down and bottom-up theories. In addition, the models that will be used to estimate these effects are more stable and have fewer assumptions than models used in previous research.

## Method

### Sample

The data in this study come from the German Socio-Economic Panel Study (GSOEP), which is an ongoing, nationally representative, household panel study that began in 1984. Households in Germany were contacted using a multi-stage random sampling technique (this sampling strategy varied somewhat for the various sub-samples, see Haisken-De New & Frick, 2003, for more details). Response rates varied from 60% to 70% across sub-samples. Haisken-De New and Frick reported that the demographic characteristics of the samples are similar to the characteristics of the general populations from which they were drawn, demonstrating that the survey coordinators were successful in selecting a representative sample. A random 95% sub-sample of respondents is available to researchers outside of Germany and only sample sizes from this 95% sub-sample are reported below.

The full sample comprises multiple sub-samples, each of which was added at different points in the study. Samples A and B (the initial samples) consist of 11,610 residents of the former West Germany and 4,229 foreigners living in Germany. Sample C consists of 4,229 residents of the former East Germany, and this sample was added in 1990. Sample D consists of 1,028 immigrants living in Germany and was added in 1994 and 1995. In 2000, a refreshment sample of 10,324 residents of Germany was added. Finally, in 2002, a sample of 2,536 residents with very high incomes was added.

Participants were surveyed yearly in face-to-face interviews. A variety of techniques were used to ensure continued participation (including providing information about the survey and giving small gifts), and attrition rates were generally very low. Among the participants who began the survey in 1984, yearly attrition ranged from a high of 13.9% (from the first to the second year) to a low of 4.3%. Average yearly attrition was 6.2% per year. Yearly attrition rates among groups that started the survey in later years were similar to the group that started in 1984, ranging from 3.6% to 11.8% per year (Lucas et al., 2003).

To limit the complexity of the models that will be tested, only the first five waves were used and only respondents from Sample A were included. In addition, because of the large sample size, analyses were restricted to individuals with complete data (though all models were also replicated using full information missing data analysis and results changed only slightly). Because questions about job satisfaction were only asked of those individuals who had jobs, the sample was restricted to individuals who had jobs in each of the first five waves. The final sample consisted of the 2,451 respondents (1,603 of which were men) with complete data. Samples sizes varied somewhat in models with additional exogenous variables.

## Measures

### Satisfaction

Early in the survey, participants were asked a variety of questions about their satisfaction with various domains in their life. The set of questions was preceded by the following lead-in: "How satisfied are you today with the following areas of your life? Please answer by using the following scale, in which 0 means totally unhappy, and 10 means totally happy. If you are partly happy and partly not, select a number in between." Participants were then presented with a list of domains (which varied somewhat from year to year) and asked to respond using the 11-point scale. The domains of interest (all of which were presented in each of the first five waves) were health, income, house/apartment, job, and leisure time.

At the end of the survey, participants were asked a single question about their life satisfaction as a whole. Participants were again asked to use an 11-point scale that ranged from 0 ("totally unhappy") to 10 ("totally happy").

### Exogenous Predictor Variables

A variety of exogenous predictor variables were included in the models to determine whether external factors were related to global and domain satisfaction scores. These measures were selected to represent relatively objective measures of the conditions in people's lives. For some domains, this choice was relatively straightforward. For instance, the natural log of total monthly household income was used as an exogenous predictor variable when examining income satisfaction. In other cases, multiple variables were available, and only the most objective were chosen for analysis. For instance, although participants' overall evaluation of their health was available in some waves, this measure was not included because it is relatively subjective. Instead, a set of much narrower health-related variables was included. Although it is possible that participants misremember or do not tell the truth about these variables, they are theoretically objectively verifiable and easily reported.

As an exogenous predictor of health, four variables were used. First, participants were asked the total number of times they had visited a doctor in the past three months. In some waves, respondents were simply asked to indicate the total number of visits; in other waves, respondents were presented with a list of specific types of doctors (e.g., dermatologist, cardiologist, etc.). In waves where specific information was available, the total number of visits was summed across all categories. Participants were also asked whether they had been admitted to the hospital in the past year, and if so, how many times. In addition, participants were asked whether they had been certified as being unable to work because of a disability. If they responded affirmatively, they were asked to indicate the degree of disability on a scale that ranged from 0% to 100%. Finally, in four out of five waves, participants were asked to report how many days of work they had missed due to illness in the past year. Because all variables were skewed, log transformations were used. The four items (doctors visits, hospital visits, disability status, and sick days) were then standardized and averaged to create an overall measure of health.

A single exogenous housing satisfaction predictor was created based on a variety of characteristics of the dwelling. Specifically, respondents were asked 10 questions about their dwelling, including the year it was built, the size of the dwelling (in square meters), the number of rooms larger than 6 square meters, and whether the dwelling had a kitchen, an indoor bath or shower, an indoor toilet, central heat, a balcony, a basement, or a garden. All variables from the same wave were entered into a principal components analysis. A single factor was extracted, and principal component scores were saved. This process was repeated for each of the five waves.

The exogenous predictor variable corresponding to leisure satisfaction consisted of two questions: The number of hours worked per week and the number of vacation days that a person took over the past year. Responses were standardized and averaged to create a single indicator for each wave.

Finally, a variety of job characteristics were combined to create an overall index measuring the quality of one’s job. In all waves, the precise occupation that respondents held was recorded. Occupations were then coded for prestige using Ganzeboom et al.,'s (1996) internationally comparable measure of occupational status. In addition, in two of the five waves (1985 and 1987), employed respondents were asked to report on a variety of job characteristics, including (a) whether the job included variety, (b) whether the job was physically demanding, (c) whether the respondent was able to determine how the work was done, (d) whether the amount of time the respondent spent working was dependent upon the amount of work that was available, (e) whether the respondents productivity was closely supervised, (f) whether the respondent did shift work, (g) whether the respondent regularly worked the night shift, (h) whether the respondent regularly came into conflict with the supervisor, (i) whether the respondent got along with his or her co-workers, (j) whether the respondent had input into company policies (including raises and promotions for other workers), (k) whether the worker could acquire skills that could be used for future advancement, (l) whether the respondent was exposed to undesirable working conditions (cold, heat, wetness, chemicals, or gases), and (m) whether the job was mentally strenuous. For each characteristic, respondents indicated whether the condition applied, partly applied, or did not apply to their job. Principal components analyses were conducted on all variables within each wave, a single factor was retained for each wave, and component scores were saved. Because job characteristics were available in only two of the waves, only two indicators were available. Attempting to model an underlying latent trait led to estimation problems, and therefore, the two component scores were averaged and used as an observed exogenous predictor of job satisfaction. Thus, models that include this exogenous predictor have fewer degrees of freedom than models with latent exogenous predictors because there are fewer observed variables.

One concern about the exogenous predictor of job satisfaction is that some of the measured job characteristics are more objective than others. For instance, one's perception that he or she experiences conflict with a boss or with coworkers is more likely to be influenced by subjective perceptions than is an external rating of job prestige. To address this concern, I examined the component loadings to see whether the retained component was determined primarily by objective factors or subjective factors. The highest loading variable was the external rating of occupational prestige whereas the lowest loading variables were the most subjective (getting along with one's boss and one's coworkers). In fact, the loadings for these more subjective variables tended to be very close to zero in all waves. Thus, the composite indicator appears to tap relatively objective characteristics of one's job.

None of these exogenous variables is meant to be an exhaustive indicator of the conditions within the domain that respondents are asked to rate. For instance, the exogenous health predictor (which consists of doctors visits, hospital visits, disability status, and sick days) clearly does not capture everything about one's health status. Thus, correlations between these variables and corresponding domain satisfactions would not be 1.00, even if respondents created satisfaction judgments in purely bottom-up way. However, these predictors can help determine whether global and domain specific satisfaction ratings correspond to objective conditions in people's lives.

## Analytic Strategy

Hierarchical LST models were used to analyze these data. Figure 1 presents a simplified version of the model that was tested. The latent state-trait model is similar in concept to the more familiar multitrait-multimethod model. Because multitrait-multimethod models and their variants are difficult to estimate, it is often not possible to include a model with the same number of method or occasion factors as the number of methods or occasions that were used. However, Eid (2000) showed that models that exclude one method factor result in stable, identified models with easily interpretable parameters. In a sense, one occasion or method is chosen as a reference to which the other methods or occasions can be compared. Schermelleh-Engel et al. (2004) extended this technique to hierarchical latent state-trait models with multiple constructs. Following their advice, I modeled all six latent trait factors (five domain satisfaction factors and one life satisfaction factor) and four occasion factors. The first occasion was set as the reference occasion, and indicators from this occasion were not linked by a separate occasion factor (Schermelleh-Engel et al.).

Because there is only one indicator per occasion, method factors could not be modeled and random error could not be separated from systematic occasion- and domain-specific variance. Thus, residual variances contain random error plus any other variance that is not attributable to the other factors. However, variance attributable to occasions can be separated from stable variance attributable to trait-like domain satisfaction. This stable domain satisfaction can be further decomposed into variance that is shared with other satisfaction measures and variance that is unique to each facet. Dispositional top-down theories posit that much variance in satisfaction measures can be attributed to a stable general factor. State-based top-down theories posit that occasion-specific variance links various satisfaction measures. Bottom-up theories predict that substantial amounts of unique variance will exist in domain satisfaction ratings.

Model testing proceeded in the following stages. First, a basic measurement model was tested. Each indicator was allowed to load on one satisfaction factor. In addition, each indicator except the indicators from the first wave were allowed to load on one occasion factor. In models that included exogenous predictors, each indicator was allowed to load on the corresponding latent trait, but no links to occasion specific factors were included (these parameters were not significant when estimated). The correlations among latent occasion factors were constrained to zero; correlations among latent satisfaction factors were estimated. The fit of this model (and all others) was tested by examining the Incremental Fit Index (IFI), the Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). Models with IFI and TLI values above .90 and with RMSEA values below .08 are generally thought to be acceptable. Although I report the chi-square, I do not rely on this index as a measure of model fit. Because the sample size is so large, the chi-square is likely to be significant even with very close-fitting models.

After testing the measurement model, a hierarchical LTS model with a single higher-order satisfaction factor linking all six lower-order satisfaction facets was tested. The amount of variance that can be accounted for by this general factor can be examined to determine the effects of top-down processes.

Finally, to assess whether objective life circumstances influence domain and general satisfaction, various exogenous predictors were added to the model. Because a model with all predictors would be very complicated, a separate model was constructed for each predictor variable. As shown in Figure 1, the paths from the predictor to the higher-order trait and to the corresponding lower-order facet were included. Direct paths from the predictor to additional domains were constrained to zero. Paths from the predictor to domain satisfaction measures provide support for bottom-up models. In addition, if exogenous predictors are related to general life satisfaction, then this provides support for the idea that this general factor does simply reflect unwanted dispositional variance.

## Results

Fit indexes for the measurement model with correlated satisfaction factors are presented in the first line of Table 1. This model fit well without any model modifications, demonstrating that the basic latent trait-state structure provides a parsimonious description of the associations among these variables. Correlations among the factors are presented in Table 2. All correlations between life and domain satisfactions are moderate to strong (.53 to .70), and all correlations among domain satisfactions are moderate (.30 to .51). This pattern of correlations suggests that a higher-order factor may link the various satisfaction facets, and thus I went on to test the hierarchical LTS model.

Line 2 of Table 1 shows the fit indexes for the model in which all satisfaction facets were linked by a single higher-order factor. Again, this model fit the data well, and the specific fit indexes changed only slightly from the less constrained model. This suggests that the covariances among the various latent satisfaction traits are well summarized by a single higher-order factor. Because this model is theoretically meaningful, and because it allows for tests of the specific predictions from top-down and bottom-up theories, it was retained for further analysis.

The next step is to determine the extent to which top-down variance drives domain satisfaction measures. Because error variance has been removed from the latent satisfaction traits, this provides a particularly powerful test of top-down and bottom-up effects. Any unique variance in the domain satisfaction measures is reliable unique variance rather than unexplainable measurement error. Specifically, this is variance from same-domain indicators that is shared across all waves of data but that is not shared with variance from any other domain satisfactions measures.

The first column of Table 3 presents the percent of total variance in each latent satisfaction trait that is unique to that trait. A number of results are noteworthy. First, it is clear that these satisfaction ratings are strongly related to the global satisfaction factor and that substantial amounts of variance are shared across all latent traits. For instance, the global satisfaction factor accounts for at least 28% and up to 54% of the variance in latent domain satisfaction. However, there is also a considerable amount of unique variance in each of the domain satisfaction traits as well. For instance, 72% of the variance in leisure satisfaction is unique variance that is not shared with life or other domain satisfaction measures. Even the domain satisfaction measure that is most closely linked with general satisfaction (income satisfaction) includes 46% unique variance. Thus, domain satisfaction measures do not simply reflect global life satisfaction plus error. These measures contain substantial amounts of reliable unique variance that distinguishes them from other domain (and life) satisfaction measures.

Table 3 also shows that although domain satisfaction measures contain considerable amounts of unique variance, the latent life satisfaction trait is almost completely determined by the higher-order latent trait: the global satisfaction factor accounts for 92% of the variance in the lower-order life satisfaction factor. In some ways, this suggests that when creating life satisfaction judgments, people may not conduct an exhaustive search of the conditions in their lives. Only five domains were assessed, and it is likely that other domains would contribute additional variance if life satisfaction judgments were constructed in this way. The fact that so much of the variance is accounted for means either (a) these five domains are very important for life satisfaction, or (b) people do not rely on domain satisfactions when constructing global life satisfaction judgments.

Thus far, results show that domain satisfaction measures contain some variance that is shared with other domain satisfaction measures and some unique variance. By examining the effects of exogenous predictor variables on these components, it is possible to determine whether the shared and unique variance reflect the actual conditions in people's lives. Table 1 reports the fit indexes for the five models that include these exogenous predictors. All models fit reasonable well. The second column of Table 3 reports the direct effect of theoretically relevant exogenous predictors on domain satisfaction latent traits. The third column reports the indirect effect (through the direct effect of the predictor on the higher-order satisfaction trait), and the fourth column reports the direct effect of the predictor on the higher-order trait. These results show that objective predictors have significant effects on both the unique variance and the shared variance that make up the domain satisfaction latent traits. For instance, even though the four indicators that are used to measure objective health (doctors visits, hospital visits, disability status, and sick days) do not perfectly capture a person's health status, these variables account for over 25% of the variance in health satisfaction. In addition, the exogenous health predictor has a significant direct effect on the global satisfaction factor, explaining over 5% of the variance in this latent trait. Thus, even the shared variance is reactive to objective life circumstances.

Table 3 also shows that these effects vary for predictors from different domains. For instance, although household income is associated with income satisfaction, the effect is not as strong as the effect of health on health satisfaction. Income accounts for approximately 10% of the variance in income satisfaction. Again, however, income is related to the higher-order domain, accounting for approximately 3% of the variance. There is even one case where the effect of the exogenous predictor on the higher-order factor is stronger than the effect on the lower-order domain. In the case of job satisfaction, the exogenous predictor accounts for 2% of the variance in domain satisfaction and 4% of the variance in the higher-order satisfaction trait.

Although analyses at the latent trait level tell researchers something about the processes that underlie satisfaction judgments, it is also important to understand how these factors affect observed variables. As a final step in the analysis, I decomposed the variance in the observed variables into residual variance, occasion variance, and stable domain variance. This domain variance was further decomposed into variance attributable to the general factor and variance that is unique to that domain. Analyses were conducted for each of the last four occasions and then averaged (the first occasion was not included because occasion specific variance could not be modeled). Table 4 reports these results.

The first column shows the amount of residual variance in each measure. As noted above, this residual variance includes random measurement error along with any occasion specific variance that is not associated with other satisfaction measures. Not surprisingly, these single-item measures have a fair amount of variance that cannot be explained by the latent factors. The second column shows the amount of variance that is attributable to occasion-specific top-down effects. These results show that for all satisfaction measures, occasion-specific factors account for substantial amounts of variance. For instance, 16% of the variance in observed life satisfaction measures is occasion-specific variance that is shared with other domain satisfaction items measured at the same wave. Occasion specific variance contributes between 7% to 16% of the variance in the observed satisfaction variables. This result is important because it shows that at least part of the top-down effects that have been found in previous studies are due to effects that cannot be explained by dispositional factors. Instead, these effects are occasion specific and independent from similar effects at different occasions.

Interestingly, the estimates of the size of these occasion-specific effects from the current study are consistent with estimates of the effect of current mood on life and domain satisfaction found in Eid and Diener’s (2004) short-term LST investigation of moods and satisfaction. These researchers found that current mood accounted for approximately 10% of the variance in life and domain satisfaction measures. Thus, the occasion-specific effects found in the current study may reflect the influence of current mood on both domain and life satisfaction judgments.

The third column of Table 4 shows that approximately half of the variance in observed satisfaction variables is due to stable facet variance. Furthermore, when this variance is decomposed into unique domain satisfaction variance and variance that is shared among all satisfaction facets, the unique variance accounts for more variance than shared variance in every domain satisfaction measure except one. With income satisfaction, unique domain satisfaction variance accounts for 25% of the variance, whereas shared global satisfaction accounts for 26%. Thus, domain-specific variance tends to account for more variance than any other systematic source. It is also important to point out that these single-item measures are likely to be relatively unreliable. Thus, future investigations using multiple indicators at each occasion will be able to determine the amount of reliable variance that can be accounted for by each of the systematic sources.

These results show that although dispositional top-down effects are likely to affect domain satisfaction judgments, these are not the only sources of covariance among the various facets. In fact, the amount of variance that is accounted for by the higher-order global factor is only 4% to 12% more than the amount of variance accounted for by occasion-specific top-down effects. Thus, for researchers interested in identifying the processes underlying top-down effects, occasion-specific factors are almost as important as dispositional factors. Dispositional factors alone cannot account for the top-down patterns of associations among various satisfaction measures.

## Discussion

Previous investigations of top-down and bottom-up models of life satisfaction share a common feature: each attempted to determine the relative importance of top-down versus bottom-up processes by decomposing the covariance between domain and life satisfaction into two directional effects. Yet the quantitative models that have been used to accomplish this goal suffer from problems that limit their ability to clarify the nature of this association. Each relies on assumptions that may not be tenable. As a result, although many studies have been conducted, little progress has been made in clarifying the nature of top-down versus bottom-up effects (Sherpenzeel & Saris, 1996).

The current study used a different approach to understanding these competing models of life satisfaction judgments. Rather than attempting to clarify the causal direction of the association between a single domain satisfaction and the broader construct of life satisfaction, the quantitative models decomposed the variance in domain satisfaction into theoretically meaningful components. Specifically, latent state-trait models were used to determine the extent to which an occasion-specific factor, a stable domain-specific factor, and a higher-order general satisfaction factor contribute to the variance in domain satisfaction measures. The unique but stable variance associated with domain satisfaction measures provides evidence regarding bottom-up effects because this variance is reliable, but unshared with other satisfaction measures. In addition, separating occasion-specific shared variance from stable, cross-wave shared variance allows for more a more precise understanding of top-down effects. Although most previous research has focused on personality processes as an explanation for top-down effects, occasion-specific effects cannot be explained by dispositional factors. Thus, when these effects emerge, additional theoretical development is required. Finally, objective predictors were added to the model to determine whether the shared and unique variance components of domain satisfaction are responsive to varying circumstances in respondents' lives.

A number of important results emerged. First, in four out of the five domains examined, the single biggest systematic factor contributing to domain satisfaction judgments was the stable domain-specific unique variance. These unique factors accounted for 31% of the variance in health satisfaction, 25% of the variance in income satisfaction, 29% of the variance in housing satisfaction, 25% of the variance in work satisfaction, and 35% of the variance in leisure satisfaction. The general satisfaction factor (which reflects the variance that is shared among domain satisfactions) tended to account for somewhat less variance in these measures, ranging from 14% to 26% of the variance in the individual domain satisfaction indicators. Thus, when LST models are used to pit bottom-up effects against top-down effects, bottom-up effects account for more variance.

In addition, by including relatively objective exogenous predictors in the models, I was able to show that domain satisfactions are responsive to varying life circumstances. For instance, objective measures of health explained over 25% of the stable variance in health satisfaction, even though the health predictor that was included is an imperfect measure of health status. Objective factors were consistently correlated with their corresponding domain satisfaction measures, though these effects did vary across domains. Furthermore, most exogenous predictors were associated even with the higher-order global satisfaction factor. This suggests that the variance accounted for by this global factor overestimates the effects of unwanted top-down processes. This covariance is likely due, at least in part, to true covariance among the external life circumstances that influence life satisfaction.

Results also show that top-down effects do not result just from dispositional processes. All five domain satisfaction measures were significantly associated with occasion-specific top-down effects. In fact, the variance contributed by occasion-specific factors was not much less than the variance contributed by the higher-order global satisfaction factor. This means that dispositional processes cannot fully explain the association among domain and life satisfaction measures. Instead, unstable, occasion-specific processes also play a role. It is possible that these occasion-specific factors reflect the influence of current mood. Our estimate of the variance that can be attributed to occasion specific factors (on average, 12%) is very close Eid and Diener's (2004) estimate of mood effects on life and domain satisfaction ratings.

Together these results provide support for the idea that satisfaction measures can be used to guide public policy. In particular, the models tested in this paper show that domain satisfaction measures do not simply result from top-down, dispositional processes. Instead, results show that respondents can discriminate among various domains within their lives, and domain satisfaction ratings provide unique and reliable information about the quality of life. Domain satisfaction ratings are responsive to varying life circumstances, and each independently contributes to overall life satisfaction judgments. Although top-down processes likely play a role in both domain and life satisfaction judgments, there is enough unique variance in these measures to suggest that their inclusion in national surveys is worthwhile.

## Limitations

The major advantage of the LST approach to decomposing variance is that the models are stable and identified, and they rely on very few assumptions. No unusual constraints had to be made, and few estimation problems were encountered. However, the disadvantage is that these models are relatively data intensive. The models tested here used data from a multi-wave panel study with many thousands of respondents. Without multiple waves of data and large sample sizes, these complicated models could not be estimated. Thus, although researchers should take advantage of LST models when the data permit, these models will not be able to be used in all situations.

A second limitation concerns the nature of the measures used in this survey. An ideal LST model would include multiple traits measured on multiple occasions using multiple methods. Such a design would allow random measurement error to be separated from reliable state variance before the substantive variance decomposition began. In the current study only one measure of each satisfaction variable was available at each wave. Thus, random measurement error could not be controlled. As a result, the unexplained residual variance in the observed variables was quite high. Although much of this variance is likely to be random error (as single-item scales tend to be somewhat unreliable), the specific amount of error variance cannot be determined. Thus, it is unclear whether additional systematic factors beyond the occasion-specific, unique domain, and global satisfaction factors are needed. Future studies would be well served by including multiple indicators of each satisfaction construct at each wave.

## Future Directions

The primary contribution of the current paper is to extend investigations of top-down and bottom-up models using methods other than the traditional cross-lagged and non-recursive models. Latent state-trait models provide information about these effects that could not be gained using these earlier techniques. Yet additional quantitative models can provide further insight into the nature of these effects. For instance, studies such as the GSOEP have been conducted for long enough periods of time that hierarchical linear modeling techniques can now be used to examine within-person trends in satisfaction over time. The the current study showed that indicators measured at a single point in time share occasion-specific variance. However, the parameters of the models that I tested only allowed this factor to capture occasion-specific variance that was shared among all indicators. It is also possible that each domain contributes unique variance to life satisfaction judgments over and above other domains within a person over time. If such effects emerge, then additional bottom-up processes that cannot be identified with

LST models may exist. Future studies can address this question by modeling within-person associations among various satisfaction facets using hierarchical linear modeling techniques.

## Summary

The current paper used latent state-trait models to decompose variance in multiple waves of life and domain satisfaction measures. Results showed that top-down effects do influence judgments of domain satisfaction. However, the amount of unique variance associated with these domain satisfaction ratings suggest that respondents can discriminate among different domains and that satisfaction judgments are not made in a purely top-down fashion. In addition objective life circumstances tended to be significantly associated with domain and global satisfaction, showing that even effects that appear to be top-down may provide an accurate reflection of the conditions in one's life. Thus, satisfaction judgments have promise as an overarching indicator that can be used to tap the quality of life of a population.

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Table 1

*Fit Indexes for Latent State-Trait Models*

| Model | $\chi^2$ | df | IFI | TLI | RMSEA |
|---|---|---|---|---|---|
| Correlated Factors | 1,818.07 | 366 | .95 | .94 | .04 |
| Higher-Order Factor | 1,906.65 | 375 | .94 | .93 | .04 |
| Health predictor | 2,686.36 | 528 | .93 | .92 | .04 |
| Income predictor | 2,424.75 | 528 | .93 | .92 | .04 |
| Dwelling Predictor | 4,319.49 | 528 | .92 | .91 | .06 |
| Job Predictor | 1,862.07 | 403 | .95 | .94 | .04 |
| Leisure Predictor | 2,196.52 | 528 | .95 | .94 | .04 |

Table 2

*Correlations Among Latent Satisfaction Factors*

| Facet | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1. Life | 1.00 | | | | | |
| 2. Health | .63 | 1.00 | | | | |
| 3. Income | .70 | .45 | 1.00 | | | |
| 4. Dwelling | .56 | .30 | .50 | 1.00 | | |
| 5. Job | .61 | .40 | .51 | .45 | 1.00 | |
| 6. Leisure | .53 | .30 | .34 | .33 | .35 | 1.00 |

Table 3

*Results from Higher-Order Models*

| Trait | Unique Variance | Direct Effect of Predictor | Indirect Effect of Predictor | Effect of Predictor on Global Satisfaction |
|---|---|---|---|---|
| Life Satisfaction | 8% | .-- | .-- | .-- |
| Health Satisfaction | 61% | .51 | .12 | .23 |
| Income Satisfaction | 46% | .31 | .12 | .17 |
| Dwelling Satisfaction | 64% | .23 | .09 | .16 |
| Job Satisfaction | 57% | .13 | .12 | .20 |
| Leisure Satisfaction | 72% | .30 | .04 | .08 |

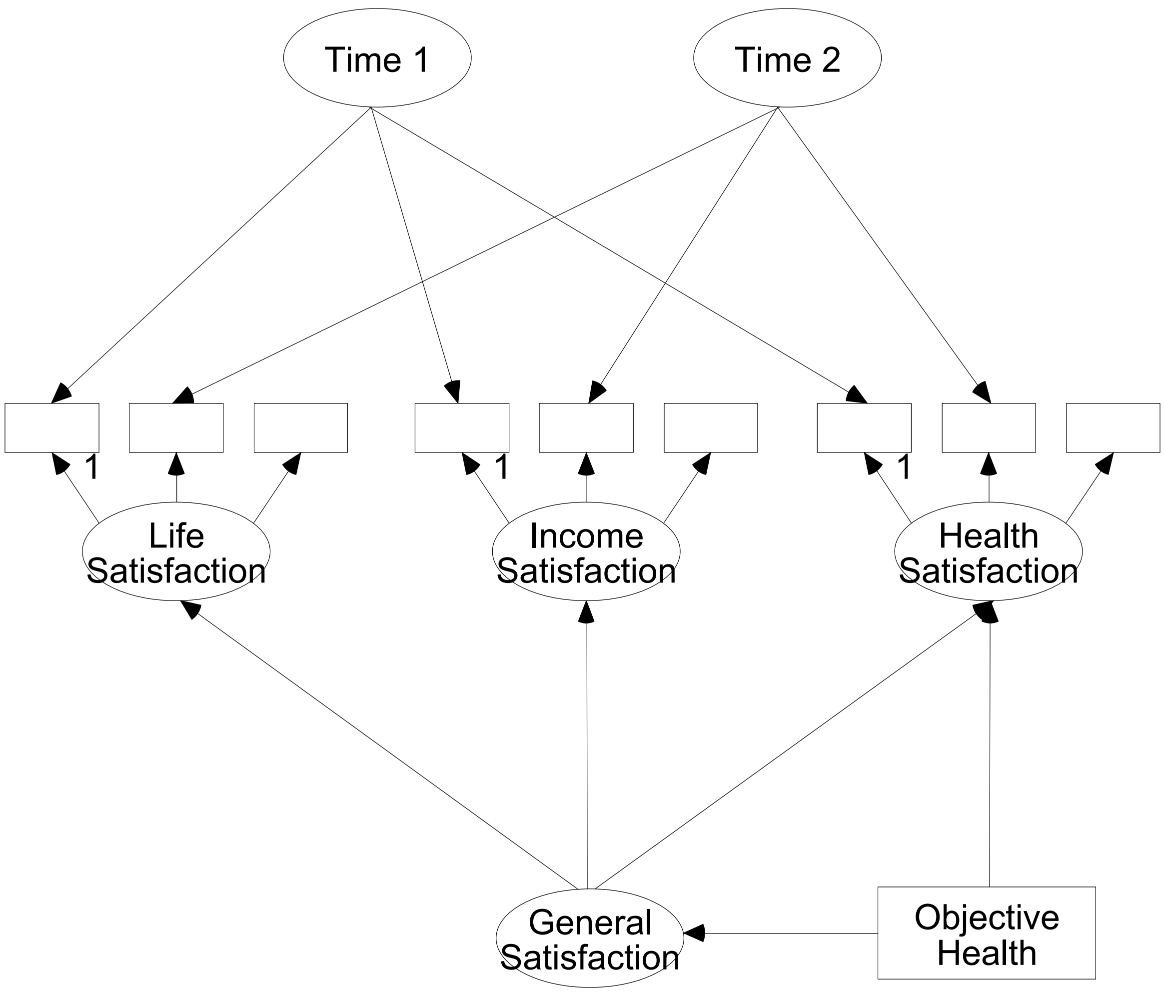
Table 4

*Variance Decomposition for Satisfaction Indicators (Averaged Across Four Occasions)*

| | | | | Domain Variance | |
|---|---|---|---|---|---|
| | Residual | Occasion | Domain | Global | Unique |
| Life Satisfaction | 40% | 16% | 43% | 40% | 4% |
| Health Satisfaction | 39% | 11% | 50% | 20% | 31% |
| Income Satisfaction | 34% | 14% | 50% | 26% | 25% |
| Dwelling Satisfaction | 44% | 11% | 45% | 16% | 29% |
| Job Satisfaction | 40% | 16% | 44% | 20% | 25% |
| Leisure Satisfaction | 45% | 7% | 48% | 14% | 35% |

Figure Caption

*Figure 1.* Simplified latent state-trait model.


Time 1
Time 2
1
1
1
Life Satisfaction
Income Satisfaction
Health Satisfaction
General Satisfaction
Objective Health