

Diverse Pathways to Positive and Negative Affect in Adulthood and Later Life: An Integrative Approach Using Recursive Partitioning

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Recursive partitioning is an analytic technique that is useful for identifying complex combinations of conditions that predict particular outcomes as well as for delineating multiple subgroup differences in how such factors work together. As such, the methodology is well suited to multidisciplinary, life course inquiry in which the goal is to integrate many interacting influences and understand subgroup variation. The authors conducted recursive partitioning analyses on a previously published study (D. K. Mroczek & C. M. Kolarz, 1998) that investigated life course profiles of positive and negative affect and incorporated various top-down (personality traits) and bottom-up (sociodemographic statuses, contextual influences) influences. The new analyses reveal multiway, nonlinear interactions among these variables in predicting affective experience and, importantly, life course differences in how these various factors combine. Included are details of how recursive partitioning trees are generated as well as descriptions of the software packages available for using such techniques. Overall, the methodology offers tractable strategies for discerning meaningful patterns in highly complex data sets.

Keywords: recursive partitioning, negative affect, positive affect, neuroticism, extraversion

Supplemental materials: <http://dx.doi.org/10.1037/0012-1649.44.2.330.supp>

The purpose of this article is to describe and illustrate a methodology, recursive partitioning, that is useful for identifying combinations of conditions implicated in particular outcomes. Our specific focus is on positive and negative affect and how they vary from young adulthood to old age and, more importantly, on what combinations of factors (sociodemographic statuses, personality traits, work and family contextual influences) account for differing levels of both kinds of affect across these periods of the life course. The objective is thus to demonstrate an analytic approach that facilitates a more comprehensive understanding of why some

experience higher or lower affective well-being as they age. Because we want to show the gains in integrative understanding that are afforded by recursive partitioning, we apply the method to previously published findings that offered a developmental perspective on happiness (Mroczek & Kolarz, 1998) using data from the Midlife in the United States (MIDUS) national survey. Key findings were that positive affect was lowest among younger adults and highest among older adults, whereas negative affect showed the reverse pattern.

Hierarchical regression analyses were used to investigate the above links between age and affect. Mroczek and Kolarz (1998) also used numerous other variables (sociodemographic factors, personality traits, contextual influences) as controls in the analytic models so as to examine the influence of aging on affective experience net of these other factors, most of which were significant independent predictors of positive and negative affect. Tests of two-way interactions between age and select control variables also revealed that some factors interacted with age in predicting levels of affect. For example, age interacted with extraversion in predicting positive affect. Age also interacted with marital status in predicting negative affect in men. Thus, the influence of some variables on affective experience appeared to differ across the life course. Analytic constraints made it difficult, however, to examine interactions of more than two variables in predicting affective experience at different stages of adulthood. This is the objective of the present analyses: namely, to use an alternative analytic technique that is designed to identify interactions of multiple variables in predicting an outcome.

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This work was supported by the John D. and Catherine T. MacArthur Foundation Research Network on Successful Midlife Development, which funded the first Study of Midlife in the United States (MIDUS), and National Institute on Aging Grants K01-AG028582 (awarded to Tara L. Gruenewald, principal investigator), R01-AG18436 (awarded to Daniel K. Mroczek, principal investigator), and P01-AG020166, which has provided support to all of the authors in continuing the MIDUS investigation.

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Specifically, we use recursive partitioning (RP) to identify particular combinations of conditions, defined by sociodemographic, personality, and contextual variables, to account for higher and lower levels of positive and negative affect at various periods in the life course. This methodology is well suited to investigations in which the goal is to consider multiple variables as simultaneously relevant to understanding particular health or well-being outcomes (Zhang & Singer, 1999) and to allow for differentiation of more than one pathway to a given outcome. To situate the inquiry in relevant previous research, we first note prior findings on aging and well-being as well as studies of top-down versus bottom-up approaches to well-being.

Aging and Well-Being

The field of aging has long been concerned with what happens to well-being as people grow older. Social gerontology was, in fact, launched as a field with prominent emphasis on whether life satisfaction and morale were affected by the aging process (Lawton, 1975; Neugarten, Havighurst, & Tobin, 1961). Initial research revealed that aging was not as strongly linked with declines in well-being as many had expected (Cameron, 1975; Larson, 1978; Shmotkin, 1990). Along the way, other indicators of well-being, such as positive and negative affect, entered into life course studies (Diener, Sandvik, & Larsen, 1985; Diener & Suh, 1997; Malatesta & Kalnok, 1984), the majority of which were cross-sectional in nature. These studies tended to show negligible differences in positive and negative affect with aging, or patterns of gain in the former and loss in the latter. National and international studies of happiness also showed fairly constant profiles across age groups (Inglehart, 1990), or even gains at least until the oldest cohorts (Davis & Smith, 1995). Bolstering these patterns, a longitudinal study, using data over 23 years, showed stability in positive affect and decreases in negative affect (Charles, Reynolds, & Gatz, 2001). However, another recent longitudinal study, using data over 10 years (although including only men), showed steady decline in positive affect and a decline in negative affect until approximately age 70, then an increase (Griffin, Mroczek & Spiro, 2006). It should be noted, however, that in both of the longitudinal investigations reviewed above, individual differences in the trajectories (intercept and rate of change) for both positive and negative affect were found, suggesting that there may be important subgroup variations in change in affective experience with age that are masked by examination of average population trajectories.

Given the general above pattern of findings, life-span developmentalists became interested in accounting for why well-being might improve with aging in several investigations. Some researchers focused on intentional actions older persons may take, such as flexibly adjusting their goal pursuits, to maintain high levels of well-being (Brandtstädter, Wentura, & Rothermund, 1999). Others suggested that older persons become more selective in their social interactions so as to optimize emotional experience (Carstensen, 1995). Yet another alternative explanation, more biologically based, is that aging may be linked with reduced physiological arousal in response to negative events (Panksepp & Miller, 1996).

For the most part, these studies of aging and affective well-being did not give much attention to the possible influence of other factors, such as gender, marital status, or educational standing,

even though these sociodemographic variables were prominent in previous research on subjective well-being (Campbell, Converse, & Rodgers, 1976). Similarly, enduring individual difference variables, such as personality traits, were also not part of most inquiries, with notable exceptions being the studies by Charles, Reynolds, and Gatz (2001) as well as Mroczek and Kolarz (1998). As reviewed below, sociodemographic, personality, and contextual variables have been given differential weight in different theoretical and empirical inquiries regarding their impact on well-being. Few studies have simultaneously examined these multiple influences within a single analysis.

Top-Down Versus Bottom-Up Approaches to Well-Being

Top-down theories of well-being assume a global tendency (derived from stable personality traits) to experience life in a generally positive or negative manner (DeNeve & Cooper, 1998; Diener, 1984). This approach led to extensive research documenting links between neuroticism and negative affect (DeNeve & Cooper, 1998; Diener & Lucas, 1999; McCrae & Costa, 1991) as well as between extraversion and positive affect (DeNeve & Cooper, 1998; Diener & Lucas, 1999; Fleeson, Malanos, & Achille, 2002; McCrae & Costa, 1991). How both traits work together in accounting for variation in well-being is rarely considered (Bardi & Ryff, 2007). In addition, studies linking personality and affect have typically not addressed life course variation in the nature of such linkages, despite Costa and McCrae's (1986) grim pronouncement years ago that those with high profiles of neuroticism in early adulthood could well anticipate not-so-successful aging.

Bottom-up perspectives of well-being, in contrast, give primary emphasis to surrounding sociodemographic factors (e.g., marital status, educational standing, income) and contextual influences (e.g., work and family strain, health status; Andrews & Withey, 1976; Campbell, Converse, & Rodgers, 1976; Diener, 1984) in understanding variation in reported levels of well-being. Objective life circumstances and quality of experience across multiple life domains thus become the basis for understanding variation in reported well-being. However, this approach has been criticized for the limited variance it explains (Diener, Suh, Lucas, & Smith, 1999). Conversely, top-down approaches have been criticized for explaining too much variance as a result of the overlap in predictor and criterion variables (e.g., using neuroticism to predict negative affect; Schmutte & Ryff, 1997).

Few have advocated for integrating top-down and bottom-up models (see Feist, Bodner, Jacobs, Miles, & Tan, 1995) to examine the interplay of traits with sociodemographic and contextual influences. This was the approach taken by Mroczek and Kolarz (1998), in which all such factors as well as select two-way interactions with age were included in regression analyses predicting positive and negative affect. So doing made it possible to assess not only the effects of age on affect but also the extent to which personality characteristics (from the top-down approach) and sociodemographic and contextual influences (from the bottom-up approach) were part of the story. The goal of the present investigation is to use an analytic approach that allows for multiway interactions among these variables as well as identifies distinct combinations of them for different subgroups of young, middle-aged, and older individuals.

Our assumptions underlying the reanalysis of Mroczek and Kolarz's (1998) data are as follows: (a) The variables included in the previous regression models are substantively relevant for understanding variation in levels of affect—that is, nothing is considered a priori as noise to be removed from analyses via statistical controls; (b) there is likely no single combination of these variables that adequately accounts for different reported levels of positive and negative affect—hence, the use of a technique that facilitates identification of multiple integrative pathways to both types of affect; and (c) how top-down and bottom-up influences come together to account for differing levels of affect may vary across the life course—thus, there is need to assess how these integrative pathways differ from young adulthood to middle and old age.

The Use of RP to Identify Combinations of Conditions That Predict Affective Experience: A Preliminary Illustration

In contrast to regression-based models, in which the primary objective is to identify an average set of conditions associated with a given outcome, RP seeks to produce a substantially more nuanced representation of the determinants of different levels of an outcome, or diverse outcomes. To orient the reader to the general

approach, we offer a preliminary example, as illustrated in Figure 1, that shows the combinations of conditions associated with differing levels of positive affect. The analysis begins with a hypothetical sample ($N = 500$) with a mean score of 20.0 on positive affect. The first question asked in the analysis is which predictor variable and what partitioning criterion would yield a division of the original 500 people into more homogeneous subgroups with distinctly different mean scores on positive affect. In this example, extraversion (with scale scores ranging from 1 to 4) is identified as the first predictor variable to be used for partitioning, with the range of mean scores collapsed into three score intervals (<2, 2–3, and >3), as shown in the figure. When considering extraversion by itself, the RP software partitions the score range (1–4) into 10 intervals and calculates the mean positive affect score for persons in each of these intervals. The program then carries out comparisons of means for adjacent levels (mean positive affect in Interval 1 vs. Interval 2; mean positive affect in Interval 2 vs. Interval 3, etc.). If the first difference is statistically significant, then the Interval 1 group is separated, or partitioned, from the other 9 groups and defined as a child node of the original population. If not, Groups 1 and 2 are pooled, and the resulting mean is compared with the mean of people in Interval 3, with this pooling and comparison process repeated until a significant dif-

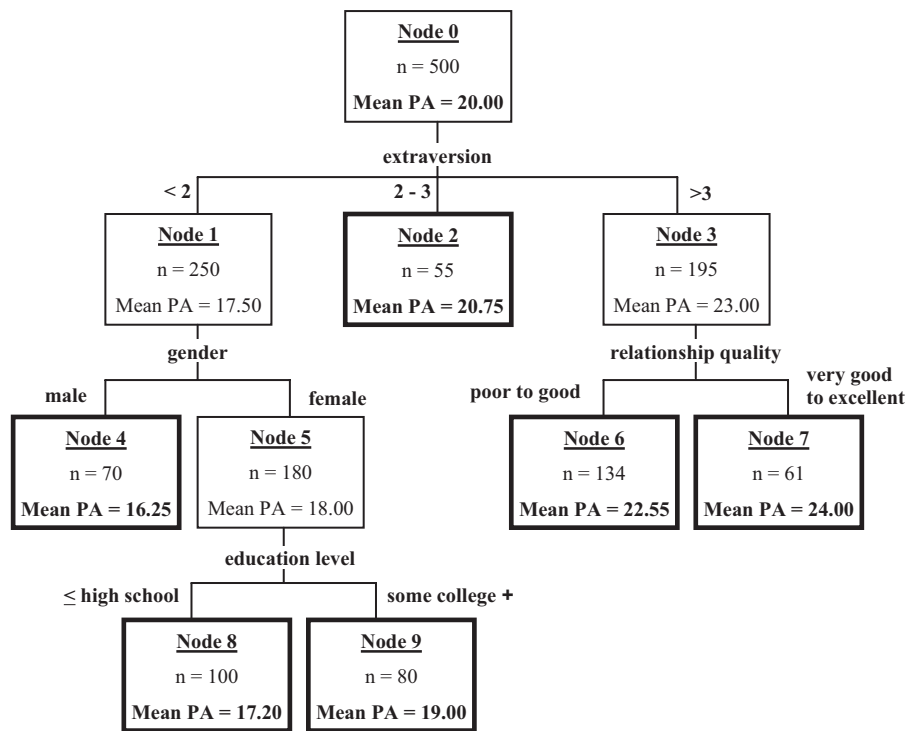


Figure 1. Hypothetical example of a recursive partitioning tree predicting mean levels of positive affect (PA) from a candidate set of nine sociodemographic (gender, marital status, education level), personality (extraversion and neuroticism), and contextual (work stress, relationship quality, financial control, health status) variables. Each node (box) in the tree specifies the mean level of PA in the group of subjects defined by the predictor variable characteristics in the branch pathway preceding the node. Terminal nodes are those at the end of a tree branch pathway and represent exhaustive and mutually exclusive groupings of sample participants as defined by the set of predictor conditions in each pathway. Each terminal node identifies the mean PA level for a specific tree pathway.

ference is found. In this hypothetical example, the result of this testing leads to pooling people in the first 5 intervals and separating them into a child node. The node contains 250 people with extraversion mean scores that are <2 and with a mean positive affect score of 17.5. Continuing this process, 55 persons with mean extraversion scores between 2 and 3 are pooled together into a second child node with a mean positive affect score of 20.75. Finally, 195 persons in the highest set of intervals of extraversion scores (those with scores >3) had a mean positive affect score of 23, which was significantly higher than the positive affect scores for persons with extraversion scores between 2 and 3. Thus, the above partitioning of extraversion provided the first variable, or branch, in what will ultimately be an RP tree.

If the tree-growing process stopped at this stage, we would have only extraversion as a predictor of positive affect, with three ranges of scores associated with three distinct levels of positive affect. However, each of these groups, or child nodes, can also be examined with regard to which variable and what partitioning criteria give the best separation of mean positive affect scores, thereby further refining the representation of predictor conditions associated with different levels of positive affect. In this example, gender yields the best partitioning of Node 1, with the male child node having a mean positive affect score of 16.25 and the female child node having a mean positive affect score of 18. There was no partition of Node 2, yielding significantly different mean positive affect scores in child nodes. However, marital or partner relationship quality yielded a further partitioning of Node 3, as shown by two child nodes with *very good to excellent* quality with a mean positive affect score of 24 and *poor to good* quality with a mean positive affect score of 22.5. Notice that with this additional level of partitioning, the range of mean positive affect scores has been extended from 16.25 to 24. Thus, the combination of conditions that yields the lowest level can now be described as persons with low extraversion and male gender, whereas the combination of conditions that yields the highest level of positive affect scores are persons with high extraversion and very good to excellent quality of relationships.

Continuing the above process one more step, Figure 1 illustrates a further partitioning of females with low extraversion (Node 5) by levels of education. However, further attempts at partitioning yield nodes with fewer than 50 people, a size we view as too idiosyncratic to be included in generating refined combinations of conditions associated with different levels of positive affect. Thus, candidate terminal nodes in the tree, with very few people in them, constitute what may be regarded as residual variation in the data.

In terms of multiple combinations of conditions leading to a common outcome, the example shows that low positive affect occurs if either of the following conditions holds:

- (a) Low extraversion (<2) AND male gender;
- (b) Low extraversion (<2) AND female gender AND at most a high school graduate

This set of conditions can also be compared to identify important variables that modulate affective experience in the presence of other variables. For example, although females with low extraversion have higher mean levels of positive affect (Node 5) as compared with males with low extraversion (Node 4), a subgroup of low extraverted females with low levels of educational attain-

ment have low levels of positive affect (Node 8), similar to those of low extraverted males. Thus, level of educational attainment is identified as a further moderator of positive affective experience among low extraverted females, but not low extraverted males.

Our illustrative example used mean scores of positive affect as the outcome, with significance (p) values from F tests used to determine whether to split or merge pairs of predictor categories on the basis of predicted mean positive affect scores. However, discrete outcome variables (e.g., high vs. low affect) can also be used, with the same basic procedure in generating trees, although in this instance the p values from chi-square tests for independence are used to specify a split. Following the above illustration, significant chi-square statistics are used to partition people into separate groups, and nonsignificant tests lead to pooling of participants.

A number of RP algorithms have been developed and implemented in a variety of statistical software programs (e.g., AnswerTree, 2006; CART, 1999; DTREG, Sherrod, 2003–2006; HelixTree & ChemTree, 2006; RTREE, Zhang, 2000). One of the most widely known and used is the Classification and Regression Tree (CART or C&RT) software developed by Breiman, Friedman, Olshen, and Stone (1984). The CART algorithms can be used with either categorical (classification) or continuous (regression) outcomes but are restricted to binary partitioning of predictor variables. The quick, unbiased, efficient statistical tree (QUEST) algorithm (Loh & Shih, 1997) is another binary partitioning technique. Alternative techniques, such as the chi-squared automatic interaction detector (CHAID; Kass, 1980) or exhaustive CHAID (Biggs, de Ville, & Suen, 1991) algorithms, can also be used to grow classification and regression trees but allow for predictor variables to be partitioned into two or more groupings or levels, such as in our illustrative example above. Although the different algorithms use different statistical tests to determine the predictor variable that will be partitioned at each level in a tree, the objective of each is to produce subgroups of participants that are homogeneous (and thus, different from each other) with respect to the target variable. A variety of tree-growing criteria, including statistical specifications for the selection of predictor variables, the minimum number of participants required in a node to allow further partitioning or to cease the partitioning process (limiting the size of the tree and the number of predictor variables in tree pathways), and techniques used to avoid overfitting the data (limiting unwieldy trees with low cross-sample replicability), are available in most RP software programs.

There are multiple advantages of using RP techniques to identify predictor conditions associated with specific levels or categories of an outcome variable of interest. One is the relative ease through which nonlinear relationships between predictor and outcome variables can be identified. Such algorithms are designed to find the cut point(s) along a categorical or continuous variable that maximally differentiates classification or scores on an outcome variable. A related advantage is the ease of identifying multilevel interactions. Although interactions can be modeled in more traditional analytic techniques, such as multiple linear and logistic regression, the complexity of doing so usually precludes the modeling of interactions of more than a few key variables. Significant interactions may also be difficult to detect in standard regression techniques because of the reduced power to find interactions as a result of needing to enter main effect terms in analyses (Aiken &

West, 1991; see also Kiernan, Kraemer, Winkleby, King, & Taylor, 2001, for an example). The identification of multiple predictor pathways that vary across sample subgroups is another advantageous feature of RP methods. For example, in our hypothetical positive affect tree, six different subgroups (represented by the Terminal Nodes 2, 4, 6, 7, 8, and 9 in Figure 1) with varying mean levels of positive affect were predicted by different combinations of predictor conditions. Another advantage of most RP algorithms is the flexibility in distributional characteristics of predictor and outcome variables—most easily incorporate categorical, ordinal, and continuous variables.

Few studies have directly compared the substantive findings that emerge from RP techniques with findings from more traditional classification or regression analytic methods. Those that have often find that RP analyses identify a similar set of significant predictor variables as compared with logistic or multiple regression (e.g., Boscarino, Galea, Ahern, Resnick, & Vlahov, 2003; Kiernan et al., 2001; see also Camp & Slattery, 2002, for discussion) but that the different methods yield different types of information regarding predictors. For example, standard multiple linear or logistic regression can provide estimation of the net effects of a specific independent variable (see Lemon, Roy, Clark, Friedman, & Rakowski, 2003, for discussion); however, such estimates represent the average effect of a predictor in the analytic sample, taking into account the impact of other predictor variables. In contrast, RP techniques are used to identify significant sets of interacting predictors that may vary among subgroups of the analytic sample, allowing for the identification of different predictor conditions in different groups of subjects. Comprehensive reviews of classification and regression tree techniques, including comparisons with other analytic methods, are available in textbooks by Breiman et al. (1984); Hastie, Tibshirani, and Friedman (2001); and Zhang and Singer (1999).

Despite the potential of RP analyses to inform questions of interest to psychologists, the use of such techniques is rare in psychological research. Some examples include identifying key psychological and sociodemographic predictors of depression (Schmitz, Kugler, & Rollnik, 2003), mental health and event-exposure predictors of posttrauma psychiatric medication use (Boscarino et al., 2003), and predictors of outpatient mental health services (Boerstler & de Figueiredo, 1991) and alcohol use (Barnes, Welte, & Dintcheff, 1991; McKenzie et al., 2006). RP techniques are also used in biomedical fields to identify risk factors for specific diseases or health conditions (Camp & Slattery, 2002; Curran et al., 1993; Falconer, Naughton, Strasser, & Sinacore, 1994; Kuchibhatla & Fillenbaum, 2003), aid clinical decision making (e.g., Barriga, Hamman, Hoag, Marshall, & Shetterly, 1996; Rudolfer, Paliouras, & Peers, 1999; Tsien, Fraser, Long, & Kennedy, 1998), and identify target audiences for health promotion interventions (Kiernan et al., 2001; King et al., 2006; Lemon et al., 2003). However, there has been little use of such techniques to inform more theoretically driven inquiries, especially in psychological research.

Thus, the objective in the present study is to use RP to examine the potential interactions of factors from both top-down and bottom-up perspectives of well-being in predicting higher or lower levels of positive and negative affect at different stages of adulthood. We predict that both theoretical perspectives have merit and thus expect that personality traits, sociodemographic characteris-

tics, and contextual variables will all have relevance in accounting for affective experience, although how they come together may vary for different subgroups of people at different stages of the life course. Thus, the aim is to gain a more integrative understanding of the interplay of these known influences on well-being and to identify varied combinations of conditions associated with differing levels of affective well-being in young, middle-aged, and older adults.

Method

Participants

Data were from a sample of 2,557 individuals who were participants in the first wave of the MIDUS Study. The MIDUS Study was based on a nationally representative sample of American adults age 25 to 74 ($M = 46$, $SD = 13$) and was conducted in 1994 to 1995. The aim of the study was to examine the social, psychological, behavioral, and sociodemographic factors associated with mental and physical well-being across the life course. All participants were English-speaking residents of the 48 contiguous states who lived in households with telephone service.

Survey data collection occurred through telephone and mail surveys. Potential participants were first contacted via phone using a random-digit dialing procedure. Information on all English-speaking adults between the ages of 25 and 74 was collected from a household informant, and then a household respondent was randomly chosen. Consenting respondents were asked to participate in a 30-min phone survey as well as to complete a self-administered questionnaire sent via mail within 1 week of the phone interview. The response rate for the first wave of the MIDUS survey for those contacted by phone was 70%, and 87% of these individuals returned the mail questionnaire, leading to a combined response rate of 61% ($70\% \times 87\% = 61\%$). A total of 3,487 individuals participated in the national random-digit dialing survey (50.6% female, 74.1% White); 3,034 of these individuals also completed the subsequent mail survey. A subsample of 2,557 individuals with complete data on variables of interest in the current study was examined in the analyses below.

Measures

A set of sociodemographic, personality, and contextual variables were examined as predictors of positive and negative affective experience. Measures were selected to parallel those used in the original study by Mroczek and Kolarz (1998).

Sociodemographic predictors of affect. Sociodemographic variables included gender (male or female), educational attainment, and marital status. Educational attainment was measured with 12 categories reflecting years of completed schooling and/or obtained educational degrees (from some grade school to graduate or professional degree). Marital status was coded as currently married or not currently married.

Personality predictors of affect. Two measures of personality traits, neuroticism and extraversion, were examined. Short measures of these traits were constructed for MIDUS with items from longer scales (see Mroczek & Kolarz, 1998, for detailed description); each scale exhibited acceptable internal consistency (neuroticism, $\alpha = .75$; extraversion, $\alpha = .79$). Respondents were asked to

indicate how well (1 = *not at all* to 4 = *a lot*) each of a set of adjectives (neuroticism adjectives: *moody, worrying, nervous, calm*; extraversion adjectives: *outgoing, lively, active, talkative*) described them. The mean of each set of items was taken to develop a neuroticism and extraversion score (possible score range for each scale: 1–4).

Contextual predictors of affect. Contextual variables included measures of relationship quality, work stress, financial control, and self-rated physical health. Relationship quality was assessed by asking the participant to rate the quality (*excellent, very good, good, fair, or poor*) of their marriage or marriage-like relationship. Participants not currently in such a relationship were given a response code of *not applicable*. Ongoing work stress was measured as the report (*yes* or *no*) of the experience of serious ongoing stress at work (e.g., extreme work demands, major changes, or other highly stressful conditions). Respondents not currently working in paid employment were given a response code of *not applicable*. Financial control was assessed by asking respondents to rate how much control (0 = *none* to 10 = *very much*) they felt they currently had over their financial situation. Self-rated physical health was measured by asking participants to rate their general physical health as *excellent, very good, good, fair, or poor*.

Positive and negative affect. Positive affect was assessed with a 6-item scale of how frequently (1 = *none of the time* to 5 = *all of the time*) the respondent felt *cheerful, in good spirits, extremely happy, calm and peaceful, satisfied, and full of life*, over the past 30 days. Negative affect was assessed as how often the respondent felt *nervous, hopeless, so sad nothing could cheer [them] up, restless or fidgety, that everything was an effort, and worthless*. Summary scores (possible range: 6–30) were created for each affective domain. These brief scales of positive affect and negative affect demonstrated acceptable internal reliability (α s = .91 and .87, respectively). More detailed information on scale development is available in Mroczek and Kolarz (1998) and Kessler and colleagues (2002).

Analyses

We used the exhaustive CHAID algorithm available in the AnswerTree (2006, Version 3.1) software program to identify predictors of negative affect and positive affect. The exhaustive CHAID algorithm was proposed by Biggs et al. (1991) and is an extension of the original CHAID technique formulated by Kass (1980). The CHAID technique determines the best split at a given node in a tree by cycling through a specified set of predictor variables to compare scores or classifications on the dependent variable as a function of pairs of categories of each predictor variable. *P* values derived from chi-square tests and *F* tests are used for categorical and continuous dependent variables, respectively. If the test value for a pair of predictor categories is not statistically significant as defined by a prespecified alpha level (e.g., $\alpha = .05$), then predictor categories are merged and the process is repeated. This pairing and merging process continues until all remaining categories are statistically different, and the resulting set of categories is the best split with respect to the predictor variable. This process is performed for all specified predictor variables. The exhaustive CHAID algorithm performs a more comprehensive examination of all available pairs of categories of a predictor, merging first the pair with the largest *p* value, repeating the category comparison process with the smaller set of

category pairs produced from the previous comparison and merge process, and terminating when only two categories remain. A Bonferroni adjusted *p* value, which corrects for the number of different ways a given predictor can be split, is calculated for all possible combinations of predictor categories. The predictor with the smallest adjusted *p* value is chosen as long as the *p* value is less than the alpha specified for splitting (e.g., $\alpha = .05$).

Predictor variables can be categorical, ordinal, or continuous in nature, with continuous variables discretized prior to analysis. The CHAID algorithm partitions continuous variables into a specific number of intervals prior to analysis, with the default set at decile partitions. To produce more coarse cuts along continuous variables (neuroticism, extraversion, education, financial control), this default was changed to tertile partitions. The rationale for forcing more coarse cuts along these variables was to avoid overfitting the data at an early stage in the tree-generation process. In preliminary analyses, we found that the strong association between neuroticism and affective variables often led to a large number of cut points on neuroticism, producing small groups in each child node that could often not be further partitioned by additional explanatory variables and that differed little from each other.

Tree-growing strategy. The single best tree identifying the predictor variables leading to varying mean levels of positive or negative affect (separate analyses were conducted for each type of affect) was examined in each of three age groups (ages 25 to 44, 45 to 64, and 65+ years). Each tree was grown in a randomly selected 60% subset of each age group ($n = 699$ in 25 to 44 year olds; $n = 652$ in 45 to 64 year olds; $n = 157$ in 65+ year olds) as the *training subsample*. Terminal nodes were specified to have a minimum number of participants approximately equal to a value representing $\geq 10\%$ of the total number of training subsample participants (terminal node $n \geq 70$ in 25 to 44 year olds; terminal node $n \geq 65$ in 45 to 64 year olds; terminal node $n \geq 15$ in 65+ year olds). A maximum of five levels below the root or parent node was specified for the tree depth, allowing up to five explanatory variables in each tree pathway that could interact to predict mean levels of positive affect or negative affect.

Split-sample validation technique. The analytic strategy produced two trees for each of the three age groups, which identified combinations of predictor variables, referred to as *pathways*, to varying mean levels of positive and negative affect, respectively. Each pair of trees was grown in a randomly selected 60% training subsample for each age group. The resulting tree structure was then applied to the remaining 40% in each age group, referred to as the *testing subsample*. In brief, the combinations of predictor variables and their respective cut points leading to a predicted mean level of positive affect or negative affect in the training sample were extracted for each pathway in each tree. These pathway specifications were exported from the AnswerTree (2006) software program into the SPSS software program. The set of predictor conditions in each pathway was applied to testing subsample participants. For each tree, this produced groups of testing subsample participants who met the same combinations of predictor variable criteria leading to specific terminal nodes as the training subsample participants. The predicted mean levels of positive affect or negative affect in each of these pathways for training and testing subsample participants were then compared with simple *t* tests to examine the predictive performance of each tree pathway. It should be noted that an automated form of this

split-sample validation technique is available in the AnswerTree program, with the exception of the statistical comparison (e.g., via *t* tests) of terminal node means across the two subsamples.

Goodness of fit. AnswerTree (2006) provides a risk estimate for each tree that assesses misclassification errors in the case of classification (categorical dependent variable) trees and average within-node error variance in the case of regression (continuous dependent variable) trees. Misclassification errors provide a straightforward estimate of the goodness of fit of a classification tree. Unfortunately, risk estimates in the form of average error variance are not as easy to intuit unless examined in the context of total model variance. One option is to use the risk estimate from a regression tree to assess the percentage of variance of the outcome variable explained by model pathways. This can be calculated with the following formula:

$$1 - \frac{\text{risk estimate}_{\text{final model}}}{\text{risk estimate}_{\text{baseline model (model with only root node)}}} \times 100$$

This formula is analogous to assessing percentage of variance explained by a model (R^2) in ordinary linear regression as $1 - (\text{sum of squares error}/\text{sum of squares total})$.¹ In the current analyses, percentage of explained variance was assessed for each tree in the training and testing samples.

Results

Descriptive statistics for each of the sociodemographic, personality, and contextual predictors of positive and negative affect are displayed, separately by each of the three age groups, in Table 1. Each group had approximately equal numbers of men and women, and the majority of respondents were married. Educational attainment was relatively equally proportioned across high school, some college, and college degree or greater groupings, with slightly greater proportions of each sample having obtained college-level educations. Most respondents who were married, or in a marriage-like relationship, reported very good or excellent relationship quality; smaller proportions reported only good, fair, or poor relationship quality. Among young and middle-aged adults, over one third reported significant ongoing stress at work, whereas work stress was reported by only a small minority of older adults, but engagement in paid work was rare in this age group. The majority of participants in each age group reported their health to be good or very good, although greater proportions of young versus older adults appeared in the more positive versus more negative rating categories, respectively. Financial control ratings were moderately high, being above the midpoint of the scale in each age group and increasing with greater age. Neuroticism scores were generally low and extraversion scores generally high in each age group.

Mean levels of positive and negative affect are also displayed at the bottom of Table 1. Levels of negative affect decreased with increasing age, whereas levels of positive affect increased slightly. Overall, mean levels of negative affect were substantially lower than mean levels of positive affect.

The results of the CHAID analyses predicting negative affect are detailed in Table 2. The table displays the predictors that appeared in the tree grown in the training subsample for each age group. Each tree pathway is detailed in a row in the table that

Table 1
Descriptive Statistics for Sociodemographic, Personality, Contextual and Affective Variables in Each Age Group

Variable	25–44	45–64	65+
Total number	1,179	1,108	270
Female (%)	49.9	50.9	48.5
Married (%)	63.2	68.2	65.9
Relationship quality			
Excellent (%)	20.3	27.8	24.4
Very Good (%)	27.6	27.3	26.7
Good (%)	15.8	11.2	10.4
Fair (%)	6.3	4.7	4.4
Poor (%)	3.4	1.7	1.5
Not applicable (%)	26.7	27.3	32.6
Work stress			
Yes (%)	39.3	33.1	4.1
No (%)	43.4	40.7	20.0
Not applicable (%)	17.3	26.2	75.9
Physical health			
Excellent (%)	15.7	15.8	12.6
Very good (%)	39.4	32.1	26.3
Good (%)	33.2	35.9	35.2
Fair (%)	9.5	12.6	20.7
Poor (%)	2.2	3.5	5.2
Education level			
≤High school degree (%)	29.0	32.2	28.1
Some college (%)	28.1	23.5	25.5
≥College degree (%)	42.9	44.3	46.4
Financial control (<i>M</i>)	6.3 (2.5)	6.8 (2.5)	7.3 (2.5)
Neuroticism (<i>M</i>)	2.3 (.7)	2.2 (.7)	2.0 (.6)
Extraversion (<i>M</i>)	3.2 (.6)	3.2 (.6)	3.2 (.5)
Negative affect (<i>M</i>)	9.9 (4.0)	9.1 (3.7)	8.5 (3.0)
Positive affect (<i>M</i>)	19.9 (4.5)	20.3 (4.4)	21.3 (3.8)

contains the combination of predictor variables and their respective cut points associated with a given mean level of negative affect. Five pathways emerged in the tree for 25 to 44 year olds. Low levels of neuroticism and not experiencing stress at work or not working (these two work categories were merged during the CHAID partitioning process) were the variables that predicted the lowest level of negative affect (Pathway 1). As can be seen in

¹ With continuous outcome variables, the described tree-growing algorithms and assessment of goodness of fit provide a close approximation to a standard least squares fitting strategy. In particular, if we let y_1, \dots, y_N denote outcome values for N individuals and x_1, \dots, x_N denote vectors of independent variables that are used in the partitioning process, then we can specify our objective as minimization of $\sum [y_i - f(x_i)]^2$, where $f(x_i) = \sum c_m I(x \in R_m); I(x \in R_m) = 1$ when x is in region R_m ; and 0 otherwise. $\{R_m, 1 \leq m \leq M\}$ is a set of regions in x space that are defined by the partitioning process, and c_m is an average of all outcome values y_i for which x_i is in the region R_m . The splitting process itself, which determines the regions R_m , proceeds by identifying, at each stage, a variable, x , and a cut point so that regions are defined by values of the variable that lie above and below the cut point and where c_m is the average of values of the outcome variable that minimizes $\sum (y_i - c_m)^2$. The last summation is over those x_i that are in region R_m . A thorough treatment of this least squares process is given in Hastie et al. (2001). The key point, for the present discussion, is that both the best split at each node and overall best fit of the resulting tree are the result of least squares minimization. It should be noted that extant software packages use efficient algorithms that approximate the ideal least squares minimization.

Table 2
Predictors of Varying Levels of Negative Affect in Each Age Group

Age group and pathway	Sex	MS	ED	NE	EXT	RQ	WS	FC	PH	Negative affect (<i>M</i>)
25-44										
1				≤2			no; N/A			7.60
2				≤2			yes			8.59
3				2-2.7						9.24
4				>2.7				6-10		11.49
5				>2.7				0-5		13.71
45-64										
1		yes		≤1.8						7.04
2		no		≤1.8						7.61
3				1.8-2.3				7-10		8.21
4				1.8-2.3				0-6		9.08
5				>2.3	>2.8					10.62
6				>2.3	≤2.8					12.87
65+										
1				≤2					very good-excellent	6.60
2	male			≤2					poor-good	7.14
3	female			≤2					poor-good	8.59
4				>2				7-10		9.03
5				>2				0-6		11.31

Note. Analyses were conducted on a random 60% training subsample in each age group. MS = marital status (married: yes/no), ED = education level, NE = neuroticism, EXT = extraversion, RQ = relationship quality, WS = work stress, FC = financial control, PH = self-rated physical health, N/A = not applicable.

Pathway 2, low neuroticism combined with the experience of work stress predicted slightly higher mean levels of negative affect. The highest level of negative affect was experienced by those with high neuroticism and low financial control (Pathway 5), whereas those with higher levels of financial control (Pathway 4) experienced slightly lower levels of negative affect. Moderate levels of negative affect were found in those with moderate neuroticism scores (Pathway 3).

Neuroticism, extraversion, financial control, and marital status appeared in the tree for middle-aged adults. Similar to young adults, low levels of neuroticism appeared in pathways leading to low levels of negative affect, with affect levels moderated by the presence (Pathway 1) or absence (Pathway 2) of a marriage or marriage-like relationship, with the lowest negative affect occurring in individuals with relationships. Levels of financial control interacted with neuroticism among those with moderate neuroticism scores, such that those with lower financial control (Pathway 4) had higher levels of negative affect than those with greater financial control (Pathway 3). Neuroticism and extraversion interacted to predict high negative affect levels: Those with high neuroticism and low extraversion had the highest reported levels of negative affect (Pathway 6), and those with both high neuroticism and high extraversion had somewhat lower levels of negative affect (Pathway 5).

Similar to young and middle-aged adults, neuroticism and financial control appeared as predictors of negative affect in the tree grown in the older adult training subsample. However, gender and physical health status also appeared in the older adult tree. Gender and physical health status interacted with low levels of neuroticism to predict varying levels of negative affect, with the lowest values in those with high levels of health status (Pathway 1), slightly higher levels occurring in older men rating their health as poor to good (Pathway 2), and the next highest levels occurring in older

women who also rated their health as poor to good (Pathway 3). Among those with high levels of neuroticism, negative affect was highest in those with lower levels of financial control (Pathway 5) and significantly lower in those with greater reported financial control (Pathway 4).

The pathways from each tree predicting mean levels of positive affect in each age group are displayed in Table 3. Neuroticism, extraversion, and financial control appeared in the tree pathways predicting positive affect in young adults. The lowest levels of positive affect occurred in those with high levels of neuroticism and low financial control (Pathway 1), and the highest positive affect levels were reported in those with low neuroticism but high extraversion (Pathway 7). Relationship quality emerged as a predictor of positive affect in middle-aged adults, along with neuroticism, extraversion, and financial control. As documented in Table 3, among those with moderate levels of neuroticism, positive affect was considerably higher in those who reported very good to excellent relationships (Pathway 4) as compared with those with lower quality relationships or no relationship (Pathway 2). In older adults, neuroticism, extraversion, financial control, and marital status appeared in tree pathways. The lowest levels of positive affect were evident in unmarried individuals with high levels of neuroticism (Pathway 1), whereas the highest positive affect levels were reported in older adults with low levels of neuroticism, high levels of extraversion, and high financial control (Pathway 5).

Summary Comparisons

Neuroticism and perceived financial control were consistent predictors of negative affect in all age groups, whereas work stress emerged only in the tree for young adults; similarly, marital status and extraversion emerged only in the tree for middle-aged adults; and gender and physical health emerged only in the older adult

Table 3
Predictors of Varying Levels of Positive Affect in Different Age Decades

Age group and pathway	Sex	MS	ED	NE	EXT	RQ	WS	FC	PH	Positive affect (M)
25-44										
1				>2.7				0-5		15.72
2				>2.7				6-10		18.32
3				2-2.7				0-7		19.39
4				<2	<2.8					20.01
5				2-2.7				8-10		21.21
6				<2	2.8-3.4					21.60
7				<2	>3.4					23.46
45-64										
1				>2.3	<2.8					16.29
2				1.8-2.3		poor-good; N/A				19.12
3				>2.3	>2.8					19.14
4				1.8-2.3		very good-excellent				21.49
5				<1.8				0-8		21.99
6				<1.8				9-10		23.65
65+										
1		no		>2						17.65
2		yes		>2						20.42
3				≤2	<3					20.88
4				≤2	>3			0-9		22.66
5				≤2	>3			10		24.58

Note. Analyses were conducted on a random 60% training subsample in each age group. MS = marital status (married: yes/no), ED = education level, NE = neuroticism, EXT = extraversion, RQ = relationship quality, WS = work stress, FC = financial control, PH = self-rated physical health, N/A = not applicable

tree. Trees predicting positive affect showed that neuroticism, extraversion, and financial control emerged in all three age groups. However, relationship quality emerged as a predictor of positive affect in middle-aged adults only, whereas marital status appeared only in the tree for older adults. Apart from these age comparisons, some variables (i.e., gender, work stress, health) appeared only in negative affect trees, whereas others (i.e., relationship quality) appeared only in positive affect trees.

Predictive Validity of Tree Pathways

To determine whether the predictor conditions in each tree pathway in the randomly generated 60% training subsamples (described above) would predict similar levels of affect in an independent group of same-age individuals, tree pathway conditions were applied to the remaining 40% testing subsample in each age group. This process involved examining the mean negative affect or positive affect levels in testing subsample groups that met all of the cut-point criteria on the combination of predictors outlined in each tree pathway in Tables 2 and 3. As documented in Table 4, in all pathways but one, the mean levels of negative affect or positive affect did not significantly differ (as compared with simple *t* tests) between the training and testing subsamples, indicating that the same predictor variable combinations led to similar levels of affect in each group. For many tree pathways, the levels of negative affect or positive affect across the two samples were remarkably similar. No restrictions were imposed as to the minimum number of participants present in each predictor pathway in the testing subsample. However, for only one pathway (Pathway 5 in the positive affect tree for 25 to 44 year olds) did the number of participants fall below the minimum of 10% of the subsample

criterion set for the training analyses (the total number of participants in this pathway represented 8% of the testing subsample), but predicted positive affect levels for this pathway did not significantly differ across the training and testing groups.

Goodness of Fit

The total variance explained (R^2) by the set of predictor conditions in each tree is noted in Table 4 and shows similar estimates across training and testing subsamples and across age groups (~23%-30%). Exceptions were for negative affect and positive affect trees applied to older adults (testing subsample), for which R^2 estimates were considerably lower (~14%-18%). Thus, analyses may not have identified an overly robust set of predictors of affect in older adults, and additional predictor variables may need to be considered in order to enhance the discriminatory power of tree models in this age group.

Discussion

The primary purpose of this investigation was to illustrate the utility of recursive partitioning, an analytic method useful for identifying complex multiway interactions among variables that are implicated in particular outcomes. We applied the technique to previously analyzed data on age differences in positive and negative affect (Mroczek & Kolarz, 1998). That investigation used multiple variables (sociodemographic factors, personality traits, contextual influences) as controls in the analytic models but also included tests of two-way interactions of select variables with age. The aim was to complement those findings with a data analytic approach that is more integrative in intent (i.e., all variables are

Table 4
Predicted Mean Levels of Negative and Positive Affect in Training and Testing Samples in Each Age Group

Age group and pathway	Training sample (M)	Test sample (M)	<i>p</i> (mean comparison)
Negative Affect			
25–44			
1	7.60	7.81	.44
2	8.59	8.11	.17
3	9.24	9.54	.38
4	11.49	12.37	.15
5	13.71	13.59	.87
% agreement	100%		
Tree R^2	27%	28%	
45–64			
1	7.04	7.04	.98
2	7.61	7.55	.87
3	8.21	8.04	.58
4	9.08	9.04	.95
5	10.62	11.35	.18
6	12.87	12.38	.60
% agreement	100%		
Tree R^2	27%	29%	
65+			
1	6.60	7.23	.17
2	7.14	7.95	.09
3	8.59	7.83	.30
4	9.03	9.29	.71
5	11.31	11.05	.84
% agreement	100%		
Tree R^2	30%	18%	
Positive Affect			
25–44			
1	15.72	16.41	.33
2	18.32	17.94	.54
3	19.39	19.23	.78
4	21.01	19.78	.76
5	21.21	21.00	.79
6	21.60	20.71	.09
7	23.46	23.05	.38
% agreement	100%		
Tree R^2	26%	23%	
45–64			
1	16.29	16.23	.94
2	19.12	20.76	.02
3	19.14	18.24	.12
4	21.49	21.11	.47
5	21.99	21.38	.18
6	23.65	24.02	.49
% agreement	83.3%		
Tree R^2	25%	23%	
65+			
1	17.65	18.80	.41
2	20.42	20.83	.64
3	20.88	21.83	.26
4	22.66	22.25	.63
5	24.58	23.55	.21
% agreement	100%		
Tree R^2	27%	14%	

Note. Tree pathways taken from trees grown in the training sample in each age group. Pathways were then applied to the testing sample and the mean levels of negative or positive affect in each pathway were estimated. Mean levels of predicted affect for each pathway were then compared for the training and testing samples using simple *t* tests. The overall level of agreement across pathways in mean affect scores in the two samples for each age group was computed as the percent of total pathways for which mean scores did not significantly differ. The percent of total variance explained by the set of pathways in each tree (Tree R^2) is noted for each subsample.

considered as substantively meaningful in accounting for affective experience) and, importantly, recognizes the variability that exists among subgroups in how such variables come together (i.e., rather than depict the average story for the sample as a whole, the aim is to delineate multiple integrative pathways). We first examine what was learned using this approach and then consider limitations and needed extensions of the findings.

The Interplay of Top-Down and Bottom-Up Influences on Affective Well-Being

As summarized in the introduction, extensive literatures have shown empirical support for top-down (i.e., traits) and bottom-up (i.e., sociodemographic standing, contextual influences) approaches to well-being. Whereas most research has pitted the two approaches against each other, our findings show how both perspectives work together to account for different levels of positive and negative affect. Further, we have clarified life course variants in the specific combinations of variables that predict affective experience. Before examining these combinations, we first note the pervasiveness of neuroticism, which appeared as the primary splitting variable in all pathways to affective experience. Numerous prior studies have documented that neuroticism predicts negative affect (DeNeve & Cooper, 1998; Diener & Lucas, 1999; McCrae & Costa, 1991), which may reflect overlapping content between predictor and criterion variables (Schmutte & Ryff, 1997), but few studies have shown that neuroticism, frequently in interaction with extraversion, also predicts positive affect. The problem is that extant research has focused almost exclusively on extraversion in predicting positive affect (DeNeve & Cooper, 1998; Diener & Lucas, 1999; Fleeson et al., 2002; McCrae & Costa, 1991), rather than considering the interplay between prominent traits (Bardi & Ryff, 2007). Thus, even before integrating top-down and bottom-up approaches, the present analyses draw attention to the neglected issue of major traits working together to account for affective experience.

Adding sociodemographic and contextual variables to the story highlights the prominence of particular factors that appear in multiple pathways to differing levels of positive and negative affect. With regard to bottom-up influences, reported financial control was the most frequently appearing contextual variable, appearing in pathways across all age groups and for both positive and negative affect. Socioeconomic status has been shown to be a strong determinant of mental and physical health (Adler et al., 1994; Anderson & Armstead, 1995), but there is a growing recognition that subjective perceptions of socioeconomic standing (i.e., the extent to which people perceived they are disadvantaged) are also predictive of health outcomes (Singh-Manoux, Marmot, & Adler, 2005). Our findings underscore the importance of perceived financial control in predicting affective experience, both positive and negative, which may in turn be consequential for mental and physical health (Gallo & Matthews, 2003). With regard to future MIDUS analyses, it would be useful to bring additional objective measures of socioeconomic status (e.g., income, occupational standing) into the above analyses to better understand the interplay among sociodemographic, trait, and contextual factors in predicting affective well-being as well as other indicators of health. RP offers a valuable analytic tool for probing interactions among these domains.

Because MIDUS includes wide age variation, we decided a priori to conduct age-stratified analyses so as to explicate life course differences in top-down and bottom-up factors that shape affective experience. That said, our inquiry was guided not so much by specific hypotheses about the exact factors that would come together in pathways for young, middle-aged, and older adults but by the aim of illustrating the value of RP for integrating top-down and bottom-up influences on positive and negative affect. Our results show that different contextual and sociodemographic factors do, indeed, work in concert with neuroticism and/or extraversion to amplify or dampen the influence of these traits on affective experience at different stages of adulthood. For example, work stress in young adulthood and health status in older adulthood interacted with neuroticism to predict varying levels of negative affect, whereas marital quality interacted with neuroticism to predict levels of positive affect in middle adulthood. Such effects likely reflect the differential centrality of these various contextual factors in young, middle, or older age. However, sociodemographic factors, such as gender and marital status, emerged to interact with neuroticism in predicting affect only in middle and later adulthood. Future empirical and theoretical work is needed to more clearly establish the interplay of such factors in modulating affective experience.

Whether our findings can be replicated remains to be seen, but our split-sample validation analyses provide some support for the predictive consistency of identified predictor conditions. In the 34 tree pathways observed, only 1 predicted a mean level of affect in the testing sample that was significantly different from the mean observed in the training sample. Thus, the analyses identified specific combinations of personality, sociodemographic, and contextual variables that appear to be robust predictors of differing levels of positive and negative affective experience. The set of predictor pathways in each tree also accounted for a modest proportion of the variance in affective outcomes.

Nonetheless, the current analyses are but a first step toward discovering what RP can elucidate regarding the multiplicity of interacting factors that lead to greater or lesser well-being. Future investigations are needed to refine this integrative understanding by using other personality traits (e.g., openness to experience, conscientiousness), other psychosocial variables (e.g., coping strategies, goal orientations), and other sociodemographic and contextual variables (e.g., income, race–ethnicity, neighborhood influences). Because studies of well-being increasingly distinguish between hedonic or happiness-like indicators and eudaimonic or life engagement and self-development indicators (Keyes, Shmotkin, & Ryff, 2002; Ryan & Deci, 2001), future investigations might also investigate additional well-being endpoints. A particular limitation of the present analysis is that the data were based on cross-sectional comparisons. Longitudinal extensions would greatly help clarify whether the above age differences reflect actual life course changes—that is, dynamic shifts in what contributes to or diminishes well-being—or, alternatively, indicate possible cohort–generational differences in how multiple factors converge to account for differing levels of positive and negative affect.

Strengths and Limitations of RP Analyses

The current analyses used a single RP algorithm—exhaustive CHAID—to identify combinations of predictor variables associ-

ated with varying mean levels of positive and negative affect. As previously noted, a variety of other RP algorithms exist that differ in the statistical methods used to select predictors, the number of allowable splitting partitions, and the types of outcome variables (e.g., nominal vs. continuous). Each algorithm is capable, however, of uncovering varied combinations of multipredictor interactions in different sample subgroups. We chose the CHAID algorithm because of our interest in identifying the predictor conditions associated with different levels of affect, all along the spectrum of negative and positive affect, and because CHAID allows for splits at more than two points along a single variable. As such, we were able to identify nonlinear interactions—that is, where one variable interacts with another at only specific levels of a given variable (e.g., physical health status predicted variations in negative affect but only in older adults with low levels of neuroticism).

Our analyses identified, separately for each age group, the single best tree composed of the most significant predictors of varying levels of negative or positive affect at each node in the tree. However, additional tree-generation techniques are possible and may yield beneficial information. One technique used successfully in previous research (e.g., Gruenewald, Seeman, Ryff, Karlamangla, & Singer, 2006; Zhang, Yu, & Singer, 2003) is the production of a *forest* of trees, in which multiple trees are created by user substitution of suboptimal (e.g., second or third best), but significant, splitting predictors at specific nodes (e.g., parent or first-level child nodes) in a given tree. The predictive validity of pathways generated from such suboptimal trees is often equivalent to that of the tree pathways produced from the inclusion of the optimal splitting predictor at each tree node, and collectively, a forest of trees can identify a larger set of predictor conditions associated with a given outcome or set of outcomes. We note the availability of alternative forest generation strategies that do not rely on subjective intervention by the analyst, such as the random forest method advocated by Breiman (2001), which can identify predictors with high predictive performance across multiple trees. However, this technique is sometimes criticized for improving predictive accuracy at the expense of interpretability (Zhang et al., 2003), which is a trade-off that is often undesirable when testing theory or attempting to understand the interplay of factors influencing a given phenomenon.

This discussion of forests highlights the user option to intervene in the tree-growing process that is available in some RP software programs. In the current analyses, trees were grown automatically by software machinery according to our predefined growing criteria (e.g., specifications regarding the size of the tree, minimum number of participants required to split a node or terminate the splitting process). However, the AnswerTree (2006) software also allows for users to intervene at multiple points in the tree-growing process, including the ability to select or change the splitting predictor at each node in a tree, change the values of predictor variables at which splits are made, and add or remove segments of a tree. Such options may be useful in testing specific theories or in producing tree pathways characterized by greater real-world plausibility or clinical relevance (e.g., Levy et al., 1985).

It should be noted that the RP algorithms are essentially forward stepwise techniques, with the selection of predictor variables appearing in the latter branches and terminal nodes affected by the selection of variables and sample subgroups occurring further up

the tree. Thus, some variables with significant impact on an outcome may be missed as a result of the sample segmentation that occurs at each level of a tree. This problem can be minimized, however, by considering trees that use second-, third-, or even fourth-best splits at a given node (as noted in our discussion of forests above) and then assessing whether an interpretable combination of conditions is produced. Prior theory may be useful to guide the forcing of particular variables into a tree, thereby enriching combinations of conditions considered.

RP is sometimes referred to as a data-mining technique because of the frequent use of such methods to identify predictors of an outcome from among a large set of candidates in which there may be no a priori hypotheses. However, as with many statistical techniques, the exploratory versus hypothesis-testing nature of a given RP analysis is determined by the user. In some instances, RP techniques may be used initially in an exploratory fashion to identify significant predictors of a given outcome, including nonlinear relationships between predictor and outcome variables as well as potential interactions among predictors, with such inquiry followed by more traditional statistical methods in which the net effect of specific predictors is the primary focus. Alternatively, RP could be used in a hypothesis-testing fashion at the outset, for example, to test for predicted life course pathways of resilience or vulnerability, defined in terms of co-occurring conditions of adversity or advantage (see Ryff, Singer, & Palmersheim, 2004; Singer & Ryff, 1999; Singer, Ryff, Carr, & Magee, 1998).

Although RP is often characterized as a *large sample*, multivariate technique, the methodology can also be very useful in analyses of small to moderate sized samples (Biggs et al., 1991; see Boscarino et al., 2003, and Levy et al., 1985, for examples), especially when there is a large ratio of predictors to cases (Zhang, Yu, Singer, & Xiong, 2001). Multiple subsample validation techniques (e.g., *k*-fold cross-validation) are also available to evaluate trees grown in small samples for which split-sample validation techniques are not feasible (Hastie, Tibshirani & Friedman, 2001). However, regardless of the overall sample size, it is the task of the analyst to specify the minimum number of participants for whom it is meaningful to identify combinations of predictor conditions (i.e., the minimum number of participants allowed in terminal nodes in a tree). This decision will be impacted by subject matter and analytic goals.

The typical use of a large number of examined predictors in RP analyses also raises the question of the impact of multicollinearity of predictors. Because of the forward stepwise nature of recursive partitioning, the algorithms are affected little by multicollinearity as is true with other forward stepwise regression techniques. This is in contrast to simultaneous (*all-in*) multiple regression methods, which can be dramatically impacted by the specific predictors entered into analyses and their associations with each other (see Kiernan et al., 2001, for discussion, and McGee, Reed, & Yano, 1984, for an example).

Finally, we note the advantages of some RP algorithms in dealing with missing data. For categorical predictors, missing data can easily be modeled as an additional category within the variables. Some RP software programs allow for the modeling of missing data as a "floating category" in analysis of ordinal or discretized continuous variables. These techniques allow for the comparison of those missing information on a given variable to those with specific values of the construct in impacting outcomes

of interest. We chose not to model missing data in the present analyses in order to use an analytic sample examined in a previous analysis by Mroczek and Kolarz (1998), but information on missing data can be incorporated into the methods presented in this overview.

Conclusions

Of particular relevance to life course studies of well-being is the capacity of RP to integrate multiple factors (in the person, the proximal situation, and the surrounding social structure context) known to influence reported well-being, and to do so in a way that delineates diverse combinations of conditions accounting for differing subgroups of respondents. As such, the methodology facilitates working in the middle territory between strictly nomothetic and idiographic approaches (see Singer et al., 1998), a challenge that has frequently eluded much social scientific and health inquiry. Such investigations thus go beyond the study of averages, both in reported levels of well-being and in what predicts them, and as such, also call for refinement in guiding theoretical frameworks. For life-span researchers, this means paying greater attention to the variability in pathways to well-being within as well as between age groups; whereas for those studying well-being and health, it requires going beyond dichotomous choices (e.g., top-down or bottom-up models) and analytic strategies that take predictive influences apart (i.e., assess effects of one variable, net of all else) rather than put them together (Ryff, in press). That is to say, the methodology we have showcased calls for greater theoretical complexity to interpret, if not predict, what is evident in the data.

In conclusion, we have tried to highlight features of RP that may be of use for those doing integrative, multidisciplinary research. We have not presented a comprehensive overview of the mathematical properties of RP algorithms, nor have we presented a thorough comparison of RP with other statistical methods and the advantages and limitations of each. Interested readers should consult a number of comprehensive reviews of RP techniques for more in-depth discussions of these topics (e.g., Hastie et al., 2001; Zhang & Singer, 1999). Our intent has been rather to underscore the turning point that may occur in scientific inquiry when unique combinations of variables are discovered to influence an outcome in important ways. The presence of one factor, a second, or a third may not matter when they occur alone. However, working in concert, such factors may nonetheless influence outcomes of interest. These multiway interactions often lurk undetected in the data because testing three-way or higher interactions is costly from the standpoint of statistical power, especially if done with ordinary regression models. RP techniques described herein offer a route to reveal these multiway interactions while also identifying combinations of co-occurring conditions that vary across population subgroups. The identification of such pathways has the potential to transform the way we approach, and understand, developmental processes, including health and well-being outcomes along the way.

References

- Adler, N. E., Boyce, T., Chesney, M. A., Cohen, S., Folkman, S., Kahn, R., et al. (1994). Socioeconomic status and health. The challenge of the gradient. *American Psychologist*, 49, 15–24.

- Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Thousand Oaks, CA: Sage.
- Anderson, N. B., & Armstead, C. A. (1995). Toward understanding the association of socioeconomic status and health: A new challenge for the biopsychosocial approach. *Psychosomatic Medicine*, *57*, 213–225.
- Andrews, F. M., & Withey, S. B. (1976). *Social indicators of well-being: America's perception of life quality*. New York: Plenum Press.
- AnswerTree (Version 3.1) [Computer software]. (2006). Chicago, IL: SPSS. Retrieved from <http://www.spss.com/answertree>
- Bardi, A., & Ryff, C. D. (2007). Interactive effects of traits on adjustment to a life transition. *Journal of Personality*, *75*, 955–984.
- Barnes, G. M., Welte, J. W., & Dintcheff, B. (1991). Drinking among subgroups in the adult population of New York State: A classification analysis using CART. *Journal of Studies on Alcohol*, *52*, 338–344.
- Barriga, K. J., Hamman, R. F., Hoag, S., Marshall, J. A., & Shetterly, S. M. (1996). Population screening for glucose intolerant subjects using decision tree analyses. *Diabetes Research & Clinical Practice*, *34*(Suppl.), S17–S29.
- Biggs, D., DeVill, B., & Suen, E. (1991). A method of choosing multiway partitions for classification and decision trees. *Journal of Applied Statistics*, *18*, 49–62.
- Boerstler, H., & de Figueiredo, J. M. (1991). Prediction of use of psychiatric services: Application of the CART (classification and regression trees) algorithm. *Journal of Mental Health Administration*, *18*, 27–34.
- Boscarino, J. A., Galea, S., Ahern, J., Resnick, H., & Vlahov, D. (2003). Psychiatric medication use among Manhattan residents following the World Trade Center disaster. *Journal of Traumatic Stress*, *16*, 301–306.
- Brandtstädter, J., Wentura, D., & Rothermund, K. (1999). Intentional self-development through adulthood and later life: Tenacious pursuit and flexible adjustment of goals. In J. Brandtstädter & R. M. Lerner (Eds.), *Action and self-development: Theory and research through the life span* (pp. 373–400). Thousand Oaks, CA: Sage.
- Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32.
- Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. I. (1984). *Classification and regression trees*. Belmont, CA: Wadsworth.
- Cameron, P. (1975). Mood as indicant of happiness: Age, sex, social class, and situational differences. *Journal of Gerontology*, *30*, 216–224.
- Camp, N. J., & Slattery, M. (2002). Classification tree analysis: A statistical tool to investigate risk factor interactions with an example for colon cancer (United States). *Cancer Causes and Control*, *13*, 813–823.
- Campbell, A., Converse, P. E., & Rodgers, W. L. (1976). *The quality of American life: Perceptions, evaluations, and satisfactions*. New York: Russell Sage Foundation.
- Carstensen, L. L. (1995). Evidence for a life-span theory of socioemotional selectivity. *Current Directions in Psychological Science*, *4*, 151–156.
- CART [Computer software]. (1999). San Diego, CA: Salford Systems. Retrieved from <http://www.salford-systems.com>
- Charles, S. T., Reynolds, C. A., & Gatz, M. (2001). Age-related differences and change in positive and negative affect over 23 years. *Journal of Personality and Social Psychology*, *80*, 136–151.
- Costa, P. T., & McCrae, R. R. (1986). Personality stability and its implications for clinical psychology. *Clinical Psychology Review*, *6*, 407–423.
- Curran, W. J., Scott, C. B., Horton, J., Nelson, J. S., Weinstein, A. S., Fischbach, A. J., et al. (1993). Recursive partitioning analysis of prognostic factors in three radiation therapy oncology group malignant glioma trials. *Journal of the National Cancer Institute*, *85*, 704–710.
- Davis, J. A., & Smith, T. W. (1995). *General social surveys, 1972–1994: Cumulative file (ICPSR 6217)* [Electronic database]. Ann Arbor, MI: International Consortium of Political and Social Research.
- DeNeve, K. M., & Cooper, H. (1998). The happy personality: A meta-analysis of 137 personality traits and subjective well-being. *Psychological Bulletin*, *124*, 197–229.
- Diener, E. (1984). Subjective well-being. *Psychological Bulletin*, *95*, 542–575.
- Diener, E., & Lucas, R. E. (1999). Personality and subjective well-being. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), *Well-being: The foundations of hedonic psychology* (pp. 213–229). New York: Russell Sage Foundation.
- Diener, E., Sandvik, E., & Larsen, R. J. (1985). Age and sex differences for emotional intensity. *Developmental Psychology*, *21*, 542–546.
- Diener, E., & Suh, E. (1997). Measuring quality of life: Economic, social, and subjective indicators. *Social Indicators Research*, *40*, 189–216.
- Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*, 276–302.
- Falconer, J. A., Naughton, B. J., Strasser, D. C., & Sinacore, J. M. (1994). Stroke inpatient rehabilitation: A comparison across age groups. *Journal of the American Geriatrics Society*, *42*, 39–44.
- Feist, G. J., Bodner, T. E., Jacobs, J. F., Miles, M., & Tan, V. (1995). Integrating top-down and bottom-up structural models of subjective well-being: A longitudinal investigation. *Journal of Personality and Social Psychology*, *68*, 138–150.
- Fleeson, W., Malanos, A. B., & Achille, N. M. (2002). An intraindividual process approach to the relationship between extraversion and positive affect: Is acting extraverted as “good” as being extraverted? *Journal of Personality and Social Psychology*, *83*, 1409–1422.
- Gallo, L. C., & Matthews, K. A. (2003). Understanding the association between socioeconomic status and physical health: Do negative emotions play a role? *Psychological Bulletin*, *129*, 10–51.
- Griffin, P., Mroczek, D. K., & Spiro, A. (2006). Variability in affective change among aging men: Findings from the VA Normative Aging Study. *Journal of Research in Personality*, *40*, 942–965.
- Gruenewald, T. L., Seeman, T. E., Ryff, C. D., Karlamangla, A. S., & Singer, B. H. (2006). Combinations of biomarkers predictive of later life mortality. *Proceedings of the National Academy of Sciences, USA*, *103*, 14158–14163.
- Hastie, T., Tibshirani, R., & Friedman, J. (2001). *The elements of statistical learning: Data mining, inference and prediction*. New York: Springer-Verlag.
- HelixTree & ChemTree [Computer software]. (2006). Bozeman, MT: Golden Helix. Retrieved from <http://www.goldenhelix.com/index.jsp>
- Inglehart, R. (1990). *Culture shift in advanced industrial society*. Princeton, NJ: Princeton University Press.
- Kass, G. V. (1980). An exploratory technique for investigating large quantities of categorical data. *Applied Statistics*, *29*, 119–127.
- Kessler, R. C., Andrews, G., Colpe, L., Hiripi, E., Mroczek, D. K., Normand, S.-L., et al. (2002). Short screening scales to monitor population prevalences and trends in nonspecific psychological distress. *Psychological Medicine*, *32*, 959–976.
- Keyes, C. L. M., Shmotkin, D., & Ryff, C. D. (2002). Optimizing well-being: The empirical encounter of two traditions. *Journal of Personality and Social Psychology*, *82*, 1007–1022.
- Kiernan, M., Kraemer, H. C., Winkleby, M. A., King, A. C., & Taylor, C. B. (2001). Do logistic regression and signal detection identify different subgroups at risk? Implications for the design of tailored interventions. *Psychological Methods*, *6*, 35–48.
- King, A. C., Marcus, B., Ahn, D., Dunn, A. L., Rejeski, W. J., Sallis, J. F., et al. (2006). Identifying subgroups that succeed or fail with three levels of physical activity intervention: The Activity Counseling Trial. *Health Psychology*, *25*, 336–347.
- Kuchibhatla, M., & Fillenbaum, G. G. (2003). Alternative statistical approaches to identifying dementia in a community-dwelling sample. *Aging & Mental Health*, *7*, 383–389.
- Larson, R. (1978). Thirty years of research on the subjective well-being of older Americans. *Journals of Gerontology: Medical Sciences*, *33*, 109–125.

- Lawton, M. P. (1975). The Philadelphia Geriatric Center Morale Scale: A revision. *Journals of Gerontology*, *30*, 85–89.
- Lemon, S. C., Roy, J., Clark, M. A., Friedmann, P. D., & Rakowski, W. (2003). Classification and regression tree analysis in public health: Methodological review and comparison with logistic regression. *Annals of Behavioral Medicine*, *26*, 172–181.
- Levy, D. E., Caronna, J. J., Singer, B. H., Lapinski, R. H., Frydman, H., & Plum, F. (1985). Predicting outcome from hypoxic-ischemic coma. *Journal of the American Medical Association*, *253*, 1420–1426.
- Loh, W. Y., & Shih, Y. S. (1997). Split selection methods for classification trees. *Statistica Sinica*, *7*, 815–840.
- Malatesta, C. Z., & Kalnok, M. (1984). Emotional experience in younger and older adults. *Journals of Gerontology*, *39*, 301–308.
- McCrae, R. R., & Costa, P. T. (1991). Adding *liebe und arbeit*: The full five-factor model and well-being. *Personality & Social Psychology Bulletin*, *17*, 227–232.
- McGee, D., Reed, D., & Yano, K. (1984). The results of logistic analyses when the variables are highly correlated: An empirical example using diet and CHD incidence. *Journal of Chronic Diseases*, *37*, 713–719.
- McKenzie, D. P., McFarlane, A. C., Creamer, M., Ikin, J. F., Forbes, A. B., Kelsall, H. L., et al. (2006). Hazardous or harmful alcohol use in Royal Australian Navy veterans of the 1991 Gulf War: Identification of high risk subgroups. *Addictive Behavior*, *31*, 1683–1694.
- Mroczek, D. K., & Kolarz, C. M. (1998). The effect of age on positive and negative affect: A developmental perspective on happiness. *Journal of Personality and Social Psychology*, *75*, 1333–1349.
- Neugarten, B. L., Havighurst, R. J., & Tobin, S. S. (1961). The measurement of life satisfaction. *Journal of Gerontology*, *16*, 134–143.
- Panksepp, J., & Miller, A. (1996). Emotions and the aging brain: Regrets and remedies. In C. Magai & S. H. McFadden (Eds.), *Handbook of emotion, adult development, and aging* (pp. 3–26). San Diego, CA: Academic Press.
- Rudolfer, S. M., Paliouras, G., & Peers, I. S. (1999). A comparison of logistic regression to decision tree induction in the diagnosis of carpal tunnel syndrome. *Computers and Biomedical Research*, *32*, 391–414.
- Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, *52*, 141–166.
- Ryff, C. D. (in press). Challenges and opportunities at the interface of aging, personality, and well-being. In E. P. John, R. W. Robins, & L. A. Pervin (Eds.), *Handbook of personality: Theory and research* (3rd ed.). New York: Guilford Press.
- Ryff, C. D., Singer, B. H., & Palmersheim, K. A. (2004). Social inequalities in health and well-being: The role of relational and religious protective factors. In O. G. Brim, C. D. Ryff, & R. C. Kessler (Eds.), *How healthy are we?: A national study of well-being at midlife* (pp. 90–123). Chicago: University of Chicago Press.
- Schmitz, N., Kugler, J., & Rollnik, J. (2003). On the relation between neuroticism, self-esteem, and depression: Results from the National Comorbidity Survey. *Comprehensive Psychiatry*, *44*, 169–176.
- Schmutte, P. S., & Ryff, C. D. (1997). Personality and well-being: Reexamining methods and meanings. *Journal of Personality and Social Psychology*, *73*, 549–559.
- Sherrod, P. H. (2003–2006). DTREG [Computer software]. Brentwood, TN: Author. Retrieved from <http://www.dtreg.com>
- Shmotkin, D. (1990). Subjective well-being as a function of age and gender: A multivariate look for differentiated trends. *Social Indicators Research*, *23*, 201–230.
- Singer, B. H., & Ryff, C. D. (1999). Hierarchies of life histories and associated health risks. In N. E. Adler & M. Marmot (Eds.), *Socioeconomic status and health in industrial nations: Social, psychological and biological pathways* (Vol. 896, pp. 96–115). New York: New York Academy of Sciences.
- Singer, B. H., Ryff, C. D., Carr, D., & Magee, W. J. (1998). Life histories and mental health: A person-centered strategy. In A. Raftery (Ed.), *Sociological methodology* (pp. 1–51). Washington, DC: American Sociological Association.
- Singh-Manoux, A., Marmot, M. G., & Adler, N. E. (2005). Does subjective social status predict health and change in health status better than objective status? *Psychosomatic Medicine*, *67*, 855–861.
- Tsien, C. L., Fraser, H. S., Long, W. J., & Kennedy, R. L. (1998). Using classification tree and logistic regression methods to diagnose myocardial infarction. *Medinfo*, *9*, 493–497.
- Zhang, H. (2000). RTREE [Computer software]. New Haven, CT: Author. Retrieved from <http://masal.med.yale.edu/rtree/>
- Zhang, H., & Singer, B. (1999). *Recursive partitioning in the health sciences*. New York: Springer.
- Zhang, H. P., Yu, C. Y., & Singer, B. (2003). Cell and tumor classification using gene expression data: Construction of forests. *Proceedings of the National Academy of Sciences, USA*, *100*, 4168–4172.
- Zhang, H. P., Yu, C. Y., Singer, B., & Xiong, M. M. (2001). Recursive partitioning for tumor classification with gene expression microarray data. *Proceedings of the National Academy of Sciences, USA*, *98*, 6730–6735.

Received January 2, 2007

Revision received September 19, 2007

Accepted October 2, 2007 ■