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Defining Past-Experience Dimensions for Wilderness Recreation

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Abstract *The past experience of wildland recreation users has been investigated in hypotheses of both causal and associative relationships. In the past, experience has been measured by asking visitors multiple questions about their past wildland recreation participation. These multiple items have then often been combined into unidimensional scales for hypothesis testing, without consistency in standardization or weighting methods. In this article, we describe the use of data from Cohutta Wilderness visitors to demonstrate principal-components and factor analysis techniques to define the experience construct for hypothesis testing. These approaches offer two ways to develop linear combinations of experience variables that maintain the multidimensionality of the experience construct during hypothesis testing and avoid questionable weighting and other combination processes. Factor analysis also offers the opportunity for understanding the underlying dimensions and theory building, if these are study objectives.*

Keywords Experience index, experience use history, factor analysis, principal-components analysis, specialization, wilderness.

The amount and frequency of past experience in a particular recreation activity and in a particular type of setting have intrigued researchers for some time. This topic has been investigated under a variety of headings, including experience use history (Schreyer, Lime, & Williams, 1984; Williams, Schreyer, & Knopf, 1990); elements of recreation specialization (Bryan, 1977; Wellman, Roggenbuck, & Smith, 1982; Williams & Huffman, 1986); and construction of a "composite index to past experience" (Hammitt, Knauf, & Noe, 1989; Hammitt & McDonald, 1983). Although some believe it to be a more complex construct than past analysis procedures would suggest (Watson, Roggenbuck, & Williams, 1991), the tendency has been to treat experience as a unidimensional concept in most analyses by combining various aspects of experience into a single parameter. This parameter is usually presented as a nominal or ordinal scale variable.

The objectives of this article are (1) to review the ways recreation experience has been combined into indexes for use as an independent variable or in associative relationships; (2) in the absence of well-grounded theory, to suggest mathematically acceptable alternatives that accurately present the effects of individual and combined experience

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elements; and (3) to promote more theory-based examinations of the experience construct.

Previous Methods of Combining Experience Into Indexes

Past Experience as an Element of Specialization

In the specialization literature, experience level is consistently one component of an overall index to leisure socialization. Besides the quantity of past experience in an activity or in a setting, elements of commitment and involvement are usually included. Most of the commitment and involvement items used, however, have an implied relationship with past experience.

Bryan (1977) included things such as preferences for techniques and settings in addition to measures of past experience in initial efforts to construct an index to specialization. Bryan found that anglers tend to move through stages in their "fishing careers" because the effects of participating in the sport and participating in different types of places are cumulative. The components of the index were combined into an ordinal scale, classifying each person as an "occasional fisherman," a "generalist," a "technique specialist," or a "technique-setting specialist."

In a follow-up to Bryan's work, Wellman et al. (1982) tested one of Bryan's hypotheses that conservation attitudes vary with specialization. This research compared attitudes toward depreciative behavior for the highest and lowest quartiles on a canoeing specialization index. The specialization index, defined primarily in terms of experience and involvement, was created by adding standardized scores (with maximum values of one) for amount of investment in canoeing, experience, and variables measuring the centrality of canoeing to the respondent's life-style. They concluded that specialization, as they measured it, offered little hope as a method of defining subgroups for analysis of attitudes. Similarly, Williams and Huffman (1986) devised a specialization index by combining scores on backpacking experience, climbing experience, and involvement. The standardization method used was a division of each subject's score for each variable by the standard deviation for each variable. The resulting index was used successfully in a measure of association with other user characteristics and unsuccessfully in an attempt to explain variation in specialization by the type of information used.

Schreyer and Beaulieu (1986) focused on the influence of the experience and commitment dimensions of specialization on the types of attributes preferred and how these attributes are structured for wildland recreation visitors. Past experience was measured using a composite index based on years of participation in wildland recreation, number of visits per year, and number of areas visited. Standardized scores were summed and the sum was categorized into low, medium, and high values. They found that the experience index and a commitment index influenced the structure of attributes preferred but that they were not related to the types of attributes preferred.

Virden and Schreyer (1988) included general experience and recent experience variables, equipment and economic variables, and centrality-to-life-style variables in a specialization index. These scores were standardized to z scores and added to obtain a specialization index. This index was found to vary with the type and importance of environmental setting desired by recreationists.

In the specialization literature, experience is obviously believed to be a central influence; it is a major dimension of the specialization concept (Schreyer & Beaulieu, 1986).

An examination of how the experience dimension is formed from individual experience elements suggests that, in most cases, methods of operationalization are not seriously flawed.

Variation in standardization of the experience element is evident, however. The statistical definition of standardization is quite specific. Standardization entails subtracting the mean and dividing by the standard deviation to produce z scores (Wonnacott & Wonnacott, 1977). Dividing only by the standard deviation results in a "scaled variable" (Draper & Smith, 1981). The variations in definitions and methods used to combine variables with unlike units could affect subsequent analyses.

Although these studies have been aimed primarily at investigating the value of specialization as a segmentation tool, there is little theoretical support for the dimensions selected to represent the concept. Within the specialization literature, there is generally little theoretical discussion of specific variables to measure and use in the composite indexes. The problem occurs when the individual elements are combined within dimensions and across the specialization index and all ability to advance and test theoretical reasoning has been lost. It is nearly impossible to draw conclusions or advance hypotheses about the contributions past experience, or any other dimension, makes to the findings of this research. Although the use of specialization indexes has proved useful in differentiating user types and recreation preferences, it really provides little understanding about why and when specialization occurs (Hammitt et al., 1989).

In most cases, the analysis emphasis has been on defining the dependent variable or the variable expected to covary with the specialization approximation (index). It appears that further theoretical development on how the specialization indexes should be formed and use of analytical methods that illustrate individual and interactive effects of the separate elements of the resulting indexes would be desirable.

Experience Use History (EUH)

This line of research has concentrated on classifying recreation visitors on multiple dimensions of past experience. Schreyer et al. (1984) and Williams et al. (1990) are recent examples of experience use history research. On the basis of previous work in this area, these researchers used the same nominal scale, EUH variable, constructed from the combination of three dichotomous ordinal scales: (1) number of times respondent floated the river, (2) number of rivers the respondent floated, and (3) number of river trips the respondent made. "Novices" were river floaters on their first trip. "Beginners" had been on 2–4 total trips on 5 or fewer rivers *or* 6–10 total trips on 4 or fewer rivers. "Locals" had taken 6 or more trips on only 1 river (study river) *or* 6 or more trips on up to 4 rivers, but 5 or more of these trips had to have been on the study river. "Collectors" had taken 6–10 trips on 5–10 rivers. "Visitors" had taken more than 10 trips total on at least 5 rivers, with at least 5 trips on the study river.

In the EUH research, even though more advanced efforts describe EUH as a multidimensional typology, the categorization of various past-experience factors into a single nominal scale reduces the construct to a unidimensional one for analysis purposes. When past-experience variables are combined into nominal scales, the ability to adequately determine individual variable effects and combined effects is essentially lost. Also, difficulty in interpretation of results is obvious. If "collectors" are found to be different from "visitors," it is not obvious which aspect of past experience accounts for this difference. The nominal scale categories used to develop the typology have limited application beyond the research being reported. Managers could not easily incorporate this information into strategies for managing the resource and others would not likely use the same typology on other rivers. Schreyer et al. (1984) concluded that the EUH research has "only identified some suggestive initial relations" (p. 47). They pointed out the need to investigate the importance of more experience dimensions than the three combined in the EUH index. They also stated that determining the most useful dimensions of experience and the relative contributions to explaining variables of importance to managers, planners, and researchers remains to be accomplished.

Composite Ordinal Indexes of Past Experience

Some studies focused on the effects of experience by developing composite ordinal indexes to an overall past-experience construct. In a study by Hammitt and McDonald (1983) designed to better understanding how past experience of river users influenced their perceptions of resource disturbance, the amount of past experience was considered a surrogate measure of user exposure to and familiarity with resources and their management. In that study, river users were classified on an ordinal scale consisting of low-, moderate-, and high-experience categories. This scale was developed by classifying subjects on a mathematical combination of four experience variables (total years floating, frequency of floating per summer, years of floating where sampled, and frequency of floating per summer where sampled), which had themselves been categorized as low, medium, and high. These categories were based on previous research findings by others and on "scientist intuition."

In a study of horseback rider preferences for facilities, programs, and services, Hammitt et al. (1989) categorized users on an ordinal scale index as having low, moderate, or high experience. The index was developed by multiplying categorical measures (low, moderate, and high) of trip frequency per year to the subject area (implying a substantial weight) by the sum of three other experience variables (times per year riding anywhere, number of years riding in wildland recreation areas, and number of times riding in wildland recreation areas in the last 5 years, implying equal weights). This classification system provided an experience index that was significantly related to visitor preferences. However, the experience index was not found to be significantly related to a user-generated self-classification of experience.

This method of operationalizing experience again tends to reduce past experience to only one dimension. Nothing from this line of study suggests that this procedure is warranted. It is mostly common sense, or "researcher intuition," that suggests to the authors what aspects of experience should be included in the composite index and how they should be combined. It also seems that basic mathematical principles are being violated when variables are categorized into ordinal scales and these ordinal values are then multiplied or added together (Schuster & Zuuring, 1986). More acceptable methods of weighting and standardization are available. Pointing out these remaining problems, Hammitt et al. (1989) concluded that "researchers need to examine new ways to better measure user experience and to explore its influence on user perception and expectations" (p. 210).

Summary of Problems Evident in Past Research

In general, the methods just reviewed tend to treat experience as a unidimensional concept. When various aspects of experience are combined, the ability to determine whether there are multiple facets of experience and how individual variables or combinations of them might influence the various dependent variables of interest is lost. The mixed findings using combined experience elements may be explained by the loss of ability to test accurately the effects of experience using these combined indexes. With such variation in mathematical procedures used and an inability to determine the relative effects of the various past experience elements, the ability to contribute to theoretical reasoning about past-experience dimensions is severely hampered. Until the knowledge base allows researchers to advance theory-based hypotheses, to guide experience item selection, and to prescribe ways to combine them, more mathematically acceptable alternatives should be examined and considered as alternatives for methods used in the past.

Alternative Methodological Approaches to Analyzing Past Experience

Two primary concerns drive the search for an improved empirical method for examining the relation between past recreation experience and visitor attitudes, motives, or preferences. First, researchers should not make seemingly unsupportable decisions about how these experience dimensions should be combined. There are very few examples in which experience has been examined in the same way in two or more studies. Combinations should be based on sound theory, empirical evidence, or both. Whatever is done should incorporate appropriate mathematical procedures. Questionable mathematical practices such as adding or multiplying ordinal data from visitor classification variables should be avoided. If unlike measures must be combined, at least accepted standardization methods should be used.

Second, it is desirable to have the opportunity for analysis to contribute to improved understanding of the experience construct. If one subjectively combines several dimensions of past experience, the various dimensions are forced into a single variable that is assumed to measure one construct. If one truly wishes to understand the effects of past experience, one should allow the opportunity to examine individual and interaction effects of the various dimensions as well as total effects. Variables that are not correlated should not be combined. Variables that are highly correlated, however, can reasonably be combined into one dimension. This knowledge could guide in theory development and in selecting variables for future research or monitoring.

An appropriate approach would use mathematically acceptable procedures to analyze the covariance (correlation) structure of multivariate data (the experience variables) to develop appropriate indexes of experience dimensions. The multivariate methods reviewed and illustrated here are principal-components analysis and factor analysis. Both hold some promise for the analytical needs typical in recreation research regarding past experience. There is an abundance of general literature on these two analysis methods. The purpose of this discussion is to demonstrate the applicability of the two methods to this particular analysis problem and to differentiate between the two approaches in terms of objectives addressed, underlying assumptions, and interpretation of results.

Demonstration Data Set

In discussing and illustrating alternatives, we present a case example. The data were obtained from a 1989 study of visitors to the Cohutta Wilderness, a 37,000-acre Forest Service wilderness in the southern Appalachian Mountains approximately midway between Atlanta, Georgia, and Knoxville, Tennessee. Visitors were surveyed from May through November. Several questions were asked pertaining to the past recreational experience of visitors. On the basis of a review of the specialization, EUH and past-experience composite ordinal index literature, investigators selected six measures of experience: (1) number of previous visits to the Cohutta, (2) number of years since the first visit to the Cohutta, (3) typical number of times per year the Cohutta is visited, (4) total number of other wilderness areas visited, (5) number of years since first wilderness visit, and (6) typical number of times per year any wilderness is visited. With approximately 67% response to a mailback survey, 440 responses provided 390 usable answers on all six experience questions.

Table 1 shows a summary of these data. One may deduce from the extremely wide ranges, differences between the mean and median, and large standard deviations that there are normality problems with the data reported. One option would have been to eliminate outliers. Outliers originate from sources such as clerical errors, miscalculations, misinterpretation of coded responses during analysis, and malfunctioning equipment (Neter, Wasserman, & Kutner, 1990; Wonnacott & Wonnacott, 1977). On examination of original responses, however, it was determined that most of these errors had not occurred. It appeared that a small number of individuals consistently reported extremely high experience at the Cohutta and low experience elsewhere, or high experience at other places and extremely low experience at the Cohutta. Most of the data, however, were skewed toward the low end of the scales. Chase and Harada (1984) reported that the percentage error of recreation participation estimates increases directly with the size of the estimate, suggesting that miscalculations by high-experience users is a possibility. The importance of including this portion of the sample in analysis, because of their unique experience patterns, outweighs the values of simply eliminating them as outliers. Distribution of these experience variables will have to be addressed in analysis methodology.

Alternative 1: Principal Components

Principal-components analysis is a numerical method used to reduce the dimensionality of multivariate data. It produces a new set of composite variables (principal components) that are orthogonal (Kim & Mueller, 1978). The construction of principal components is motivated by the desire to (1) explain a large proportion of the total variance in the original variables and (2) reveal relationships that were not previously suspected and thereby allowing interpretation (Johnson & Wichern, 1982). No assumption concerning the underlying structure of the multivariate data is required.

Principal-components analysis typically involves the following steps: (1) a correlation or covariance matrix is prepared (use a correlation matrix when units of measure are dissimilar, see Table 2); (2) the eigenvalues and the corresponding eigenvectors are extracted from the correlation or covariance matrix; and (3) principal-component scores are produced for use in further analysis, such as in regression analysis.

Eigenvalues and Eigenvectors. The principal components are exact mathematical transformations of the original variables. An example of a linear combination is

$$Y_l = a_l'X = a_{1l}X_1 + a_{2l}X_2 + \cdots + a_{pl}X_p \tag{1}$$

where Y is the principal component, the a's are elements of the eigenvectors associated with the corresponding eigenvalues of the correlation matrix, and the X's are the origi-

Table 1
Cohutta Wilderness Experience Variables

Variable	Range	*M*	*SD*	*Mdn*
No. of previous visits to the Cohutta	0–2000	16.69	104.47	2
Years since first visit to the Cohutta	0–30	4.13	6.08	1
Typical no. of visits per year to the Cohutta	0–150	3.23	9.41	1
Total no. of other wilderness areas visited	0–50	4.46	6.36	3
Years since first visited a wilderness	0–45	9.77	8.97	8
Typical no. of visits per year to any wilderness	0–150	6.46	11.19	3

Note. $N = 390$.

nal variables (Morrison, 1976). The first principal component explains the greatest amount of variation found in the original variables; it is the single best summary of linear relationships exhibited in the data. The second component is defined as the second best linear combination of variables, under the condition that the second principal component is orthogonal to the first. This process continues until the number of principal components equals the number of variables, if the correlation matrix is of full rank (Kim & Mueller, 1978). However, if principal-components analysis is successful in data reduction, the first two or three principal components will explain 80–90% of the total sample variance (Johnson & Wichern, 1982).

In the Cohutta analysis, three principal components were retained, which is a 50%

Table 2
Correlation Matrix for Cohutta Experience Variables

Variable	1	2	3	4	5	6
No. of previous visits to the Cohutta	1.000	.323	.874	−.005	.126	.711
Years since first visit to the Cohutta	.323	1.000	.341	−.041	.291	.252
Typical no. of visits per year to the Cohutta	.874	.341	1.000	−.023	.084	.724
Total no. of other wilderness areas visited	−.005	−.041	−.023	1.000	.438	.177
Years since first visited a wilderness	.126	.291	.084	.438	1.000	.315
Typical no. of visits per year to any wilderness	.711	.252	.724	.177	.315	1.000

reduction in the number of original variables (six dimensions reduced to three; (see Table 3). The three principal components explain 85.8% of the total Cohutta sample variance, with the first principal component explaining approximately 47% of the total variation and the second and third principal components explaining approximately 24% and 15%, respectively. (The variation explained by a principal component is calculated by dividing the eigenvalue by the number of variables [Johnson & Wichern, 1982].) These three principal components can replace the original variables without much loss of information. The relationship that is revealed by the principal components is difficult to interpret. It is not apparent what the relationship is between those variables receiving high eigenvector values within a principal component. For instance, it appears that a mixture of site-specific and general-experience items is very influential in the first principal component.

Principal-Component Scores. After data reduction, only the production of the principal-component scores remains. The scores are the product of the eigenvector values multiplied by the standardized values of the original data. The production of the principal-component scores for Principal Components 1–3 is illustrated at the bottom of Table 3.

The principal-component scores "replace" the original data and would be considered wilderness experience indexes. Because these scores would replace the original data, further analysis using past experience would be based on these scores.

Alternative 2: Factor Analysis

Factor analysis is commonly used as an exploratory tool to examine interrelationships among multivariate data and for data reduction, similar to principal components. In contrast to principal components, factor analysis (1) is based on a statistical model that assumes that the underlying dimensions can be represented in terms of a hypothetical causal model (Kim & Mueller, 1978), making it a particularly appropriate procedure for theory building (Stewart, 1981); (2) attempts to reproduce the observed common variance rather than the total variance; and (3) assumes that the observed multivariate data have a multinormal distribution (Morrison, 1976).

It is assumed that the observed variable is influenced by various determinants, some of which are shared by other variables in the set, whereas others are not shared by any other variable. The part of a variable that is influenced by the shared determinants is usually called *common,* and the part that is influenced by idiosyncratic determinants is usually called *unique.* Under this assumption, the unique part of a variable does not contribute to relationships among variables. It also follows from the preceding assumption that the observed correlations must be the result of the correlated variables sharing some of the common determinants. The hope is that the assumed common determinants will not only account for all of the observed relations in the data but will also be smaller in number than the variables (Harman, 1976).

Factor analysis typically involves four steps. First, the assumption of multivariate normality is reviewed and transformations applied, if necessary. Second, initial factors are extracted. Third, the initial factors are rotated to a terminal solution—the search for simple and interpretable factors. Fourth, factor scores are estimated.

Multivariate Normality. Factor analysis relies on the assumption that the variables have a multivariate normal distribution. It has proved difficult, however, to construct good overall tests of joint normality in more than two dimensions (Johnson & Wichern, 1982).

Table 3
Principal Components for the Cohutta Experience Variables

Variable	Principal Components (eigenvectors) 1	2	3
No. of previous visits to the Cohutta (X_1)	.537[a]	−.210	−.147
Years since first visit to the Cohutta (X_2)	.305	.047	.844
Typical no. of visits per year to the Cohutta (X_3)	.538[a]	−.240	−.136
Total no. of other wilderness areas visited (X_4)	.091	.688[a]	−.363
Years since first visited a wilderness (X_5)	.225	.650[a]	.238
Typical no. of visits per year to any wilderness (X_6)	.520[a]	.036	−.244
Variation explained			
Variance (eigenvalue)	2.800	1.430	.916
Proportion	.467	.238	.153
Cumulative	.467	.705	.858

Note. Principal 1 = $.537(X_1) + .305(X_2) + .538(X_3) + .091(X_4) + .225(X_5) + .520(X_6)$.
Principal 2 = $-.210(X_1) + .047(X_2) - .240(X_3) + .688(X_4) + .650(X_5) + .036(X_6)$.
Principal 3 = $-.147(X_1) + .844(X_2) - .136(X_3) - .363(X_4) + .238(X_5) - .244(X_6)$.
[a]Apparent high eigenvector values within a principal component.

Many types of nonnormality are often reflected in marginal distributions and scatterplots. For most practical work, one-dimensional and two-dimensional investigations are ordinarily sufficient (Johnson & Wicher, 1982).

Normal probability plots, Wilk–Shapiro statistics, and bivariate scatterplots were used to examine and test for normality of the Cohutta experience variables. It was determined that these six variables were nonnormal. Natural logarithm and square-root transformations were used to normalize data before further analysis.

Factor Extraction and the Number of Factors Retained. There are many factor-extraction methods (Kim & Mueller, 1978). We present a brief discussion and results for the principal factor solution method of extraction.[1] The principal factor solution is also known as "classical factor analysis" (Harman, 1976; Johnson & Wicher, 1982).

The principal factor solution uses a reduced correlation matrix that replaces the "1s"

[1]A principal-components solution of the factor model was also conducted. Johnson and Wichern (1982) discussed the differences between the principal-components solution and the principal factor solution. Stewart (1981) suggested that the choice of extraction method has little effect on the final results. We found the results to be identical; therefore, only the principal factor solution results are presented.

on the main diagonal with the communalities (Harman, 1976; Johnson & Wichern, 1982). The correlation matrix used is presented in Table 4.

The general factor model is

$$R = LL' + E \tag{2}$$

where LL' is the matrix of factor loadings (correlations between variables and factors) and E is the matrix of estimated specific variances (see Johnson & Wicher, 1982, for an in-depth mathematical treatment). The factor loadings (LL') are estimates of the shared (common) determinants, and the specific variances (E) are the estimates of the unique determinants. The factor loadings are "coefficients" of the initial factors.

There are several approaches used to determine the number of factors to retain (Johnson & Wicher, 1982; Kim & Mueller, 1978; Morrison, 1976). The most common approach retains a factor if the eigenvalue is greater than or equal to one. Another common approach, also based on the eigenvalue, plots the eigenvalues and examines the plot (scree plot) for a "break point." Factors are retained that exceed this visible break point. With the Cohutta data, both of these methods of factor retention were applied.

Two factors were retained (see Table 5). Eigenvalues for the retained factors were 2.69 and 1.75; 74% of the variation is explained by the two factors, and an extreme drop in eigenvalue magnitude was apparent from the plot of these values. The factor model was successful in reducing the dimensionality of the past-experience data and explaining a large proportion of the original variation.

Rotation. In the unrotated form (as presented in Table 5), factor constructs are highly complex because each extracted factor accounts for as much variance as possible. Because such a factor correlates substantially with many variables that are essentially uncorrelated with each other, it becomes a complex composite of unrelated things. After

Table 4
Correlation Matrix Used in Principal Factor Solution (Classical Factor Analysis)

Variable	Transformation	1	2	3	4	5	6
No. of previous visits to the Cohutta	ln	.922[a]	.846	.889	−.056	.387	.338
Years since first visit to the Cohutta	ln	.846	.793[a]	.642	−.065	.192	.172
Typical no. of visits per year to the Cohutta	ln	.889	.642	.841[a]	−.091	.411	.359
Total no. of other wilderness areas visited	ln	−.056	−.065	−.091	.613[a]	.542	.613
Years since first visited a wilderness	$\sqrt{\ }$	.387	.195	.411	.542	.663[a]	.975
Typical no. of visits per year to any wilderness	ln	.338	.172	.359	.613	.975	.614[a]

[a]Communalities.

Table 5
Principal Factor Solution (Classical Factor Analysis) Factor Loadings

Variable	Factor Loadings[a]	
	Factor 1	Factor 2
No. of previous visits to the Cohutta	93[b]	−31
Years since first visit to the Cohutta	78[b]	−30
Typical no. of visits per year to the Cohutta	83[b]	−31
Total no. of other wilderness areas visited	22	80[b]
Years since first visited a wilderness	41	70[b]
Typical no. of visits per year to any wilderness	55	58
Variation explained		
Variance	2.686	1.751
Proportion	.448	.292
Cumulative	.448	.740

[a]Printed values are multiplied by 100 and rounded to the nearest integer.
[b]Apparent high loading within each component.

this factor is removed, the second factor will become a complex composite of what is left in the matrix of residuals (Comrey, 1973).

To derive unambiguous factor constructs from a factor analysis, if it is at all possible, it usually requires that the original extracted factor loading matrix be rotated. The rotated solution is mathematically equivalent to the universal solution. Rotation is desirable to provide interpretability by reducing the number of high loadings associated with each factor (see Harman, 1976, for an in-depth presentation on rotation).

The varimax-rotated factor loadings for the principal factor solution (see Table 6) illustrate the rotational effect. For all factor loadings found in Table 6, the large factor loadings have increased, whereas the small factor loadings have decreased. This is what was expected from varimax factor rotation.

The rotated factor loadings presented in Table 6 allow factor interpretation. The factors are very distinct with a minimal amount of overlap. The lack of overlap has made the factor interpretation quite simple. Factor 1, with large loadings on number of previous visits to the Cohutta, years since first visit to the Cohutta, and typical number of visits per year to the Cohutta, can be labeled Past Experience to the Specific Site. Factor 2, with large loadings on total number of other wilderness areas visited, years since first visited a wilderness, and typical number of visits per year to any wilderness can be labeled General Wilderness Experience. Although this may seem like a commonsense separation of variables, it should be noted that elements from these two different factors are commonly combined in unidimensional indexes (see, e.g., Patterson & Hammitt, 1990). Because they form two distinct dimensions, they should not be combined. Further analysis of similar experience dimensions at other wilderness areas should also be conducted to see whether these two dimensions appear consistently. This would be an example of an opportunity for theory building about consistency in experience patterns across visitors to wilderness areas across different regions of the country.

Factor Scores. Factor analysis is sometimes used as a means of defining groups of variables before they are combined into an index (Williams & Huffman, 1986). This research takes that concept a step farther by using the derived factors as experience constructs and generating experience indexes.

The estimated values of the experience indexes, called factor scores, can be generated in an analytical or subjective fashion. The analytical approach begins by using the rotated factor loadings to estimate the factor score coefficients. The factor score coefficients and the standardized values of the original variables are then multiplied to produce factor scores (see Johnson & Wichern, 1982, for a mathematical derivation of factor score coefficients and factor scores). The subjective approach uses the groups (factors) defined by the rotated factor loadings. Variables in those groups with large loadings are assigned factor score coefficients of one; variables with small factor loadings are assigned factor score coefficients of zero. The scores for that factor are then formed by summing the standardized observed values of the variables that were assigned a factor score coefficient of one.

The analytically and subjectively determined factor score coefficient matrixes are presented in Table 7. In both cases, the large factor score coefficients correspond to the variables with large factor loadings. This indicates they will have the most effect on the final values of the factor scores.

Table 6
Principal Factor Solution Varimax-Rotated Factor Loadings

Variable	Rotated Factor Pattern[a]	
	Factor 1	Factor 2
No. of previous visits to the Cohutta	98[b]	9
Years since first visit to the Cohutta	83[b]	5
Typical no. of visits per year to the Cohutta	89[b]	6
Total no. of other wilderness areas visited	−13	82[b]
Years since first visited a wilderness	9	80[b]
Typical no. of visits per year to any wilderness	26	76[b]

[a]Printed values are multiplied by 100 and rounded to the nearest integer.
[b]Apparent high loading within each component.

Table 7
Principal Factor Solution Factor Score Coefficients

Variable	Analytically Derived Factor Score Coefficients		Subjectively Derived Factor Score Coefficients	
	Factor 1	Factor 2	Factor 1′	Factor 2′
No. of previous visits to the Cohutta (X_1)	.850	.008	1.0	0.0
Years since first visit to the Cohutta (X_2)	.051	−.029	1.0	0.0
Typical no. of visits per year to the Cohutta (X_3)	.112	−.038	1.0	0.0
Total no. of other wilderness areas visited (X_4)	−.033	.372	0.0	1.0
Years since first visited a wilderness (X_5)	−.014	.344	0.0	1.0
Typical no. of visits per year to any wilderness (X_6)	−.045	.328	0.0	1.0

Note. Factor 1 = $.850(X_1) + .051(X_2) + .112(X_3) + .033(X_4) - .014(X_5) - .045(X_6)$.
Factor 2 = $.008(X_1) - .029(X_2) - .038(X_3) + .372(X_4) + .344(X_5) + .328(X_6)$.
Factor 1′ = $1.0(X_1) + 1.0(X_2) + 1.0(X_3) + 0.0(X_4) + 0.0(X_5) + 0.0(X_6)$.
Factor 2′ = $0.0(X_1) + 0.0(X_2) + 0.0(X_3) + 1.0(X_4) + 1.0(X_5) + 1.0(X_6)$.

Conclusions

Deciding on the appropriate method of examining the influence of the recreation experience construct is not as simple as a single prescription. As everyone hates to hear, "it depends." Apparently, it depends on the objectives one has for looking at past experience. If one wants to learn something about past experience, or how the influences of the different dimensions of past experience vary across areas, time, or subgroups of visitors, it appears that factor analysis would provide the most insight into the underlying hypothetical construct. The factor analysis method also gives one a mathematically correct method to develop an index without researcher bias or guesses about appropriate weightings.

On the other hand, if the interest is merely in developing an index using items one believes are related but there is no real interest in understanding the hypothetical construct, principal-components analysis provides the tool to objectively combine variables in an exact mathematical fashion. Using this approach, past experience is represented by orthogonal dimensions (principal components) that are combinations of experience items. There are no underlying assumptions about the distribution of the data, and some interpretation of the principal components is possible but limited.

When one examines the past research on experience, reviewed earlier in this article, it is not always clear which of these alternative analysis methods would have been best. It is clear that either method offers advantages over the methods commonly used. For the specialization studies, a more reasonable approach might have been to develop principal components from the individual items used in the specialization indexes. This would have allowed researchers to look at single effects and combined effects for the various components in explaining differences in motivation structures, etc. If, however, the interest is in understanding the hypothetical relationships between elements of experience or between the various element classifications of specialization, factor analysis could provide a basis for highlighting the individual factors that contribute to specialization, as well as provide a more appropriate method of empirical development of indexes.

The same applies to the EUH and composite index strains of experience research literature. Hammitt and McDonald (1983) did not really express an interest in improved understanding of the experience construct. There were no apparent concerns or hypotheses expressed to draw conclusions beyond the effects of "experience" in a general sense. In this case, principal-components procedures would have sufficed for superficial treatment of experience, concentrating on the combined effects of the components on the dependent variable.

In the future, or in any reexamination of some of the literature cited here, there would be an advantage of establishing, a priori, a more precise statement of reason for examining the effects of the experienced construct. If one is primarily interested in developing indexes, with little interest in understanding underlying dimensions, principal-components analysis would be an excellent choice. If, however, one is also interested in understanding the underlying dimensions of experience through knowledge of the strengths of these dimensions, factor analysis is necessary and will allow the same type of hypothesis testing that principal-components analysis would allow.

Although these mathematical procedures offer advantages over past index development methods used, emphasis should be placed on more theory-based approaches of selecting items and combining them. Through more appropriate and consistent analysis methods, progress in theory development is more likely to occur.

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