Human Dimensions of Wildlife, 14:448–455, 2009
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ISSN: 1087-1209 print / 1533-158X online
DOI: 10.1080/10871200903032580

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Research Note

Testing a Self-Classification Measure of Recreation Specialization Among Anglers

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Measuring the behavioral, cognitive, and affective dimensions of recreation specialization typically requires multiple variables such as participation, equipment, centrality, and skill. Recent research has tested more efficient approaches such as single-item self-classification measures. This research note extends this approach to fishing and tests the utility of a three-category self-classification measure of specialization (Type I: generalist, casual; Type II: intermediate; Type III: specialist, veteran) by comparing it to a more traditional 16-variable measure of the concept. Data were obtained from onsite surveys of anglers at Lost Lake in Oregon. Consistent with a specialization continuum, respondents who classified themselves as Type I anglers (generalist, casual) reported the lowest mean responses on all variables measuring centrality, skill, equipment, and experience. Type III anglers (specialist, veteran) had the highest scores. Discriminant analysis showed that the specialization variables correctly classified 88% of Type I, 92% of Type II, and 71% of Type III anglers. Overall, 88% of respondents were correctly classified. These findings suggest that a self-classification measure may perform just as well as more traditional complex multivariate techniques for measuring specialization.

keywords recreation specialization, self-classification, fishing, discriminant analysis

Introduction

Recreationists are heterogeneous, exhibiting a range of motivations, skills, attitudes, and behaviors (see Manning, 1999; Needham & Rollins, 2009 for reviews). Given this diversity, researchers have emphasized the importance of differentiating activity participants into meaningful homogeneous subgroups to avoid describing an average recreationist who does not actually exist (Shafer, 1969; Vaske, Beaman, Stanley, & Grenier, 1996). The concept of recreation specialization has received considerable attention as an approach for

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segmenting recreationists into subgroups based on "a continuum of behavior from the general to the particular, reflected by equipment and skills used in the sport and activity setting preferences" (Bryan, 1977, p. 175). At one end of this continuum are novices or infrequent participants who do not consider the activity to be a central life interest or show strong preferences for equipment and technique. The other end includes more avid participants who are committed to the activity and may use more sophisticated methods. Recreationists are hypothesized to progress to higher stages along this continuum, reflected by increasing participation, skill, and commitment (Bryan, 1977; Needham, Vaske, Donnelly, & Manfredo, 2007; Scott & Shafer, 2001).

Most researchers agree that specialization is multidimensional, consisting of behavioral, cognitive, and affective components (McFarlane, 2004; Scott & Shafer, 2001). Indicators of the behavioral dimension include equipment investment and previous participation experience (e.g., Ditton, Loomis, & Choi, 1992). Cognitive indicators include skill level and knowledge about the activity (e.g., Needham, Rollins, & Vaske, 2005). Indicators of affective attachment and commitment include centrality to lifestyle and enduring involvement (e.g., McIntyre & Pigram, 1992). There is little consensus, however, about how best to measure recreation specialization (Scott & Shafer, 2001). Both single-item (e.g., frequency of participation; Ditton et al., 1992) and multidimensional approaches (e.g., Bricker & Kerstetter, 2000) have been used to measure the concept. Studies have then classified recreationists along a linear continuum and treated this continuum as continuous or segmented it into halves, thirds, or quartiles to represent degrees of specialization (e.g., low, medium, high; Dyck, Schneider, Thompson, & Virden, 2003). Recognizing that all dimensions of specialization may not increase linearly in similar fashion over time, some researchers have used multivariate statistics such as cluster analysis to classify and describe different subgroups in an activity (Needham et al., 2007; Scott & Thigpen, 2003).

One methodological issue with most of these studies is that examining each dimension of specialization (i.e., behavioral, cognitive, affective) typically necessitates asking respondents to answer multiple survey questions about their participation, equipment, skill, and other aspects of their commitment and involvement. This could be problematic because some surveys (e.g., onsite, telephone) should be relatively short to minimize disruption of user experiences (Vaske, 2008). One approach for reducing respondent burden is to use a single-item self-classification measure of specialization. This approach presents respondents with a few categories describing combinations of various dimensions of specialization in an activity, and then asks respondents to select a category that most accurately describes them even if they do not identify with all criteria in the category. Recent research with birders (Scott, Ditton, Stoll, & Eubanks Jr., 2005), ultimate frisbee players (Kerins, Scott, & Shafer, 2007), and scuba divers (Sorice, Oh, & Ditton, 2009) has found self-classification measures to be effective for segmenting recreationists along a continuum of specialization because the measures are easier to administer, analyze, and interpret.

This research note is methodological in nature and has two objectives that build on this recent research. The first objective is to use a self-classification measure of specialization and extend this approach to fishing. The second objective is to test the utility of the self-classification measure by comparing it to a more traditional multivariate measure to assess whether the single-item approach accurately discriminates among various degrees of angler specialization.

Methods

Data were obtained from surveys of anglers at Lost Lake, which is a relatively small (15 acre) and remote lake located in Clatsop State Forest in northwest Oregon, south of highway

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26 and Elsie. Surveys were administered onsite from July to October 2006. Access to this lake in 2006, however, was limited, especially on weekdays due to resurfacing of the gravel forest access roads and active logging operations on these roads. As a result, only 74 surveys were completed (response rate = 92%) and results may not be representative of all Lost Lake visitors.

Two approaches measured respondents' specialization in fishing. First, a traditional multivariate approach measured affective, cognitive, and behavioral dimensions. Consistent with past research (Barro & Manfredo, 1996; Needham et al., 2007), the survey included 16 variables measuring centrality to lifestyle (affective), skill level (cognitive), and equipment and past experience (behavioral). Variables and response scales are provided in Table 1. Second, a self-classification measure asked respondents to classify themselves as one of three types of anglers:

Type I: "Fishing is an enjoyable, but infrequent activity that is incidental to other travel and outdoor interests. I am not highly skilled in fishing, rarely read fishing articles, and do not own much fishing equipment beyond the basic necessities."

Type II: "Fishing is an important, but not exclusive outdoor activity. I occasionally read fishing articles and purchase additional equipment to aid in fishing, my participation in fishing is inconsistent, and I am moderately skilled in fishing."

Type III: "Fishing is my primary outdoor activity. I purchase ever-increasing amounts of equipment to aid in fishing, go fishing every chance that I get, consider myself to be highly skilled in fishing, and frequently read fishing articles."

Respondents were asked which category best described them. Categories in this self-classification measure embody affective, cognitive, and behavioral dimensions of specialization, and are similar to those used in previous studies (e.g., Scott et al., 2005; Sorice et al., 2009). The categories are analogous to a continuum of specialization from generalist or casual anglers (Type I) to more specialist or veteran anglers (Type III). In total, 36% of respondents classified themselves as a Type I angler (i.e., generalist, casual), 51% were Type II anglers (i.e., intermediate), and 13% considered themselves to be a Type III angler (i.e., specialist, veteran).

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Results

Table 1 shows the mean responses and alpha reliability coefficients for the 16 variables measuring the specialization dimensions. Cronbach alpha values were .86 for centrality (five variables), .83 for skill (five variables), and .81 for equipment (five variables), suggesting that the variables reliably measured their respective dimension. Deletion of any variable from its dimension did not improve reliability. Past experience was measured with a single variable (proportion of life spent fishing). Reliability of the overall specialization index was high at .84.

Respondents who classified themselves as Type I anglers (i.e., generalist, casual; 36%) reported the lowest mean responses on all 16 variables measuring centrality, skill, equipment, and experience; Type III anglers (i.e., specialist, veteran; 13%) had the highest scores (Table 2). Type II anglers' (i.e., intermediate; 51%) responses fell between these two groups. Mean responses to "participation in fishing is a large part of my life," for example, were 2.62 for Type I anglers, 3.58 for Type II anglers, and 4.57 for Type III anglers on a scale of 1 "strongly disagree" to 5 "strongly agree." ANOVA with Least Significant Differences (LSD) and Games-Howell post-hoc tests showed that responses differed significantly among the three self-classification groups, $F = 4.88$ to 28.12, $p = .012$

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Table 1
Reliability analyses of specialization dimensions and variables

Specialization dimensions and variables	*M*	*SD*	Item total correlation	Alpha (α) if deleted	Cronbach alpha (α)
Centrality[1]					.86
If I stopped fishing, an important part of my life would be missing	3.90	1.12	.56	.86	
I would rather go fishing than do most anything else	3.37	.97	.81	.79	
Participation in fishing is a large part of my life	3.41	1.02	.85	.78	
Most other recreation activities do not interest me as much as fishing	2.98	.99	.55	.85	
Fishing is becoming a more central part of my life each year	3.10	.90	.61	.84	
Skill					.83
Given the fishing skills I have developed, it is important that I continue to participate in fishing[1]	3.78	.80	.63	.79	
I feel that I am more skilled in fishing than other anglers in general[1]	3.12	.83	.70	.77	
Testing my fishing skills is very important to me[1]	3.27	.91	.58	.81	
In general, I am becoming more skilled in fishing each year[1]	3.51	.89	.62	.79	
I would rate my skill level in fishing as …[2]	2.09	.95	.59	.80	
Equipment[1]					.81
I have accumulated a lot of fishing equipment	3.78	.82	.75	.73	
I have invested a lot of money in fishing equipment	3.67	.99	.77	.72	
I feel that I have more fishing equipment than other anglers in general	2.96	.98	.48	.81	
I often spend time learning about newest fishing equipment available	2.63	.93	.56	.79	
In general, I am obtaining more fishing equipment each year	3.35	.88	.47	.81	
Past experience (%)[3]	63.5	27.2	—	—	—
Overall specialization index					.84

[1]Variables coded on 5-point scale: 1 = strongly disagree, 2 = disagree, 3 = neither, 4 = agree, 5 = strongly agree.
[2]Variable coded on 5-point scale: 0 = beginner, 1 = novice, 2 = intermediate, 3 = advanced, 4 = expert.
[3]Variable calculated as: (number of years fished in life/age * 100) = proportion of life spent fishing (%).

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Table 2
Responses to specialization variables and dimensions for each self-classification group

Specialization dimensions and variables	Self-classification group[1] Type I	Type II	Type III	*F*-value	*p*-value	Effect size (η)
Centrality[2]						
If I stopped fishing, an important part of my life would be missing	2.94 [a]	4.27 [b]	4.71 [b]	14.12	< .001	.62
I would rather go fishing than do most anything else	2.81 [a]	3.46 [b]	4.29 [c]	7.41	.002	.49
Participation in fishing is a large part of my life	2.62 [a]	3.58 [b]	4.57 [c]	15.45	< .001	.63
Most other recreation activities do not interest me as much as fishing	2.69 [a]	2.88 [a]	4.00 [b]	5.37	.008	.44
Fishing is becoming a more central part of my life each year	2.88 [a]	3.00 [a]	4.00 [b]	4.88	.012	.42
Skill						
Given the fishing skills I have developed, it is important that I continue to participate in fishing[2]	3.25 [a]	3.92 [b]	4.43 [b]	8.13	.001	.51
I feel that I am more skilled in fishing than other anglers in general[2]	2.44 [a]	3.31 [b]	4.00 [c]	16.28	< .001	.64
Testing my fishing skills is very important to me[2]	2.75 [a]	3.38 [b]	4.00 [b]	6.20	.004	.46
In general, I am becoming more skilled in fishing each year[2]	2.88 [a]	3.73 [b]	4.14 [b]	8.73	.001	.53
I would rate my skill level in fishing as …[3]	1.21 [a]	2.48 [b]	3.00 [c]	28.12	< .001	.73
Equipment[2]						
I have accumulated a lot of fishing equipment	3.06 [a]	4.04 [b]	4.43 [b]	15.15	< .001	.63
I have invested a lot of money in fishing equipment	2.94 [a]	3.92 [b]	4.43 [b]	10.11	< .001	.55
I feel that I have more fishing equipment than other anglers in general	2.31 [a]	3.04 [b]	4.14 [c]	13.10	< .001	.60
I often spend time learning about newest fishing equipment available	2.13 [a]	2.69 [b]	3.57 [c]	7.70	.001	.51
In general, I am obtaining more fishing equipment each year	2.81 [a]	3.58 [b]	3.71 [b]	5.25	.009	.43
Past experience (%)[4]	43.15 [a]	71.70 [b]	87.11 [c]	13.67	< .001	.60

[1]Type I analogous to generalist or casual; Type II analogous to intermediate; Type III analogous to specialist or veteran. Cell entries are means unless specified otherwise. Entries with different letter superscripts across each row differ at $p < .05$ using Least Significant Differences (LSD) or Games-Howell post-hoc tests.
[2]Variables coded on 5-point scale: 1 = strongly disagree, 2 = disagree, 3 = neither, 4 = agree, 5 = strongly agree.
[3]Variable coded on 5-point scale: 0 = beginner, 1 = novice, 2 = intermediate, 3 = advanced, 4 = expert.
[4]Variable calculated as: (number of years fished in life/age * 100) = proportion of life spent fishing (%).

Table 3
Discriminant analysis predicting specialization self-classification

Function	Eigenvalue	Percent variance	Canonical correlation	Wilks' Lambda	χ^2-value	*p*-value
1	1.80	96.7	.802	.336	48.47	< .001
2	.06	3.3	.242	.942	2.68	.445

Table 4
Discriminant function coefficients and equality of group means predicting specialization self-classification

	Function 1 statistics				
Discriminant variables	Unstandardized coefficient	Standardized coefficient	Wilks' Lambda	*F*-value	*p*-value
Centrality index	.181	.116	.614	14.45	<.001
Skill index	.950	.500	.444	28.85	<.001
Equipment index	.901	.457	.510	22.11	<.001
Past experience	.017	.376	.703	9.72	< .001

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to < .001. Eta (η) effect size measures ranged from .42 to .73, suggesting large (Cohen, 1988) or substantial (Vaske, 2008) differences among these groups.

Discriminant analysis was conducted to determine how well the multiple specialization dimensions predicted responses to the self-classification measure. The maximum number of functions generated by discriminant analysis is usually one less than the number of groups in the dependent variable (i.e., self-classification measure). Discriminant analysis generated two functions (i.e., three specialization types minus one) where function 1 explained 97% of the variance and function 2 only explained 3% (Table 3). Canonical correlations were .802 for function 1 and .242 for function 2, and the eigenvalue for function 1 was 1.80 and statistically significant at $p < .001$, whereas it was only .06 and insignificant for function 2, $p = .445$. A large and significant eigenvalue suggests that more variance in the dependent variable is explained by that function. Wilks' lambda was $U = .336$ for function 1 and $U = .942$ for function 2; the smaller lambda for function 1 suggests that this function was most important to the discriminating ability (Vaske, 2008; Table 3). Taken together, these results suggest that function 2 explained little beyond that accounted for by function 1, so only function 1 was examined further.

Table 4 shows that centrality, skill, equipment, and experience each significantly predicted the self-classification measure, $F = 9.72$ to 28.85, $p < .001$. Standardized and unstandardized coefficients indicate the relative importance of these independent variables in predicting group membership for the dependent self-classification measure (Vaske, 2008). Skill (standardized coefficient = .500) and equipment (.457) had the most discriminating ability in predicting membership (Table 4). Group centroids were all relatively far apart (–1.709, .499, 2.054), suggesting that the specialization dimensions discriminated effectively among Type I, II, and III anglers, and that these three groups were distinct from each other (Table 5). The specialization dimensions correctly classified 88% of Type I anglers, 92% of Type II anglers, and 71% of Type III anglers. Overall, 88% of respondents were correctly classified (Table 5).

Table 5
Discriminant analysis classification results and group centroids

	Predicted group membership (%)[1]			
Actual group selection	Type I	Type II	Type III	Group centroids
Type I	87.5	3.8	0.0	–1.709
Type II	12.5	92.3	28.6	.499
Type III	0.0	3.8	71.4	2.054
Total	100.0	100.0	100.0	

[1]Total correctly classified = 87.8%. Type I: generalist, casual; Type II: intermediate; Type III: specialist, veteran.

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Discussion

Consistent with research on other activities (Kerins et al., 2007; Scott et al., 2005; Sorice et al., 2009), findings suggest that a relatively short and simple self-classification measure of specialization may perform just as well as more traditional complex multivariate techniques for measuring the concept. Patterns in bivariate relationships between the self-classification measure and each scale variable and dimension coupled with the high percentage of respondents correctly classified suggest that self-classification approaches may be appropriate. Self-classification measures are useful because they are relatively easy to administer, minimize respondent burden, do not require advanced knowledge of multivariate statistical techniques to analyze and interpret, and provide a more intuitive approach by allowing participants to classify themselves instead of forcing researchers or statistical programs to segment users into groups (Scott et al., 2005).

One issue with self-classification approaches is that their categories tend to reflect a continuum of progression in specialization. In this study, for example, survey descriptions of Type I anglers emphasized low participation, centrality, equipment, and skill; Type III described high achievement in each attribute. Research has shown, however, that trajectories of dimensions are not identical and progress in each dimension does not always increase linearly from low to high (e.g., Needham et al., 2007; Scott et al., 2005). Some recreationists, for example, participate regularly and become committed to an activity, but exhibit low skill; others partake infrequently, yet display attributes of skill and commitment. Asking respondents to select from an exhaustive list of categories describing all possible combinations of dimensions and attributes, however, would increase the response burden that self-classification measures are designed to minimize. Conjoint and stated choice modeling that use subsets of combinations to predict all possible alternatives may be useful for designing self-classification measures. Although these measures should continue to embody multiple dimensions of specialization (e.g., cognitive, affective), more research building on work by Kerins et al. (2007) is needed to identify and examine alternative combinations of dimensions within categories defining self-classification measures.

Findings presented here are limited to a small sample of anglers at a relatively remote lake in northwest Oregon. Additional research with a larger sample of anglers at this lake is needed to confirm findings. Applicability of these methods and findings to other activity groups and geographical areas also remains a topic for further empirical investigation. Researchers are encouraged to examine these and other issues to improve reliability, validity, and application of self-classification measures and other approaches for measuring recreation specialization.

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