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RECOGNIZING SALTWATER RECREATIONAL ANGERS' MOTIVATIONS USING MULTILAYER PERCEPTRON NEURAL NETWORK

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ABSTRACT

The purpose of this study was to examine saltwater recreational anglers' answers to the fifteen statements regarding the importance of fishing trips, and to classify groups exhibiting common patterns of responses from individuals' recreational fishing motivations using the data extracted from the database collected from the 2013 National Saltwater Angler Survey. Using the factor analysis, the fifteen statements were reduced into five dimensions, named catch, information, site preferences, social, and management. Empirical results based on the k-means clustering analysis identified three different saltwater recreational angler groups, named catch and social, site choice, and fishing related groups. Results of the discriminant analysis indicated that cluster means were significantly different. The multilayer perceptron neural network model was utilized as a predictive model in deciding the classification of saltwater anglers based on recreational fishing motivations. From an architectural perspective, it showed a 15-9-3 neural network construction. This study may provide insight into the information about what types of saltwater recreational anger groups exist and identifying unknown groups in the data set for saltwater recreational fishing planning and management purposes.

Contribution/Originality: This study integrated factor analysis, k-means clustering analysis, discriminant analysis, and multilayer perceptron neural network to provide insight into the information about what types of saltwater recreational anger groups exist regarding the importance of fishing trips for saltwater recreational fishing planning and management purposes.

1. INTRODUCTION

Marine recreational fishing is a popular pastime across the nation that generates significant economic impacts to both local and national economies. In order to recognize the importance of saltwater recreational fishing, National Saltwater Recreational Fisheries Policy released by NOAA Fisheries as the national guidance emphasizes to develop and maintain endurable and sustainable high-quality saltwater recreation fisheries in the U. S. (NOAA Fisheries, 2015).

According to the National Surveys of Fishing, Hunting, and Wildlife-Associated Recreation, the number of American fished dropped from 34.1 million in 2001 to 30.0 million in 2006, increased to 33.1 million in 2011, and increased continuously to 35.8 million in 2016. The total number of anglers participated in saltwater fishing activities dropped from 9.5 million in 2001 to 7.7 million in 2006, increased to 8.9 million in 2011, and decreased to

8.3 million in 2016 (U.S. Department of the Interior Fish and Wildlife Service and U.S. Department of Commerce U.S. Census Bureau, 2002, 2007, 2012, 2018).

In 2016, anglers fished 13 days and 11 fishing trips on average, while saltwater anglers fished 9 days and 7 fishing trips on average. Overall, anglers spent an average of $1,290 on fishing-related expenses, but saltwater anglers had an average expenditure amount of $739, an average of $82 per day. Anglers spent a total of $46.1 billion in 2016. Of the total fishing expenditures spent by anglers, anglers spent $21.7 billion on trip-related costs, $21.1 billion on fishing equipment, and $2.4 billion on other fishing expenditures (U.S. Department of the Interior Fish and Wildlife Service and U.S. Department of Commerce U.S. Census Bureau, 2018).

Among anglers, saltwater anglers spent $11.2 billion on their fishing trips and equipment in 2016. They spent a total of $6.2 billion on trip-related costs – $2.3 billion on food and lodging, $1.1 billion on transportation costs, and $2.8 billion on other trip costs such as equipment rental, bait, and guide fees; and a total of $5.0 billion on fishing equipment – $2.7 billion on equipment (rods, reels, etc.), $291 million on auxiliary equipment (camping equipment, binoculars, etc.), and $2.1 billion on special equipment such as boats, vans, and so forth (U.S. Department of the Interior Fish and Wildlife Service and U.S. Department of Commerce U.S. Census Bureau, 2018).

A growing number of research studies has adopted market segmentation approach to analyze recreational anglers' fishing motivations and preferences (Ardahan, 2012; Chi, 2006; Connelly, Brown, & Knuth, 2000; Hunt, Hutt, Grado, Neal, & Mischke, 2010; Kuehn, Durante, Brincka, Luzadis, & MacNeill, 2013). Based on angler preferences for different types of fishing opportunities, Connelly et al. (2000) identified six distinct segments from a mail survey of New York fishing license holders. Among these six segments, the two largest segments preferred a mix of fishing opportunities, three groups had varying levels of interest in boating, and the last group generally preferred fishing in tributaries for coldwater species.

Using the data extracted from the 2004 Louisiana Fishing Survey, Chi (2006) identified three different angler clusters – *Leisure*, *Sports*, and *Competitive* – tracked the motivations of anglers on the Red River. *Leisure* anglers, in this study, were more likely than the *Sports* and *Competitive* angler clusters to view the social and experiential components of their fishing experience as very or extremely important. *Competitive* anglers were the most active of the three clusters, with more days of fishing overall and more days of angling in the Red River than other anglers. They also placed a higher importance on skill-oriented aspects of the fishing experience, such as winning a trophy, testing equipment, and development fishing skills.

Hunt et al. (2010) used a market segmentation approach to divide survey respondents, freshwater angler who was selected from the license files of the Mississippi Department of Wildlife, Fisheries, and Parks, into groups based on their expressed interest in different fee-fishing opportunities. Among the survey respondents, there were 59% of anglers indicated interest in daily fee lakes, 49% of anglers indicated interest in annual lease lakes, and 32% of anglers indicated interest in fish-out ponds. Ardahan (2012) employed a 21-item Recreational Fishing Motivation Scale to identify six sub-factors, included socialization, rest and being in nature, competition and glory, escape, eat, and give, from 359 volunteer participants who live in all around of Turkey. It revealed that Recreational Fishing Motivation Scale was a reliable and valid scale in the estimation of the motivational factors for recreational fishing in Turkish population.

In order to provide detailed information that can be used for future Lake Ontario sportfishing marketing efforts, Kuehn et al. (2013) used a survey of anglers residing within the seven Lake Ontario counties in New York State to compile three largest resident angler groups: no preference, smallmouth bass, and largemouth bass anglers. For the no preference anglers, the primarily motivations were to fish by enjoyment, nature appreciation, and affiliation. For the smallmouth bass anglers, they were primarily motivated to fish by enjoyment, nature appreciation, affiliation (i.e., spending time with others), personal achievement (i.e., success at catching fish and improving skills), and nurturing others into the sport. For the largemouth bass anglers, the fishing motivations were to fish by enjoyment, nature appreciation, affiliation, and personal achievement; nurture, escape, and satisfaction with catch were moderate motivations.

Very few detailed studies have been carried out on understanding how saltwater anglers perceive recreational fishing motivations and specifically on the classification of this interest group of saltwater anglers using advanced techniques. The main purpose of this paper was to classify saltwater anglers based on their fishing motivations using neural networks. Specifically, this paper tried to explore segmentation of the saltwater angler population based on certain perceives of interest regarding recreational fishing motivations, and to investigate how saltwater anglers' behavior can be identified using neural networks, based on information obtained from traditional surveys. Furthermore, by learning to recognize the current and past trends of saltwater fishing activities and behavior of saltwater anglers, neural networks could make prediction in future outcomes within a campaign.

This paper also made an estimation of the size of saltwater angler subgroups that have been identified, which may be useful for saltwater recreational fisheries managers to prioritize and effectively allocate marine fisheries management initiatives and resources. Thus, this study may provide insight into the information about what types of saltwater recreational anger groups exist and identifying unknown groups in the data set for saltwater recreational fishing planning and management purposes. It may also contribute to a better understanding of current and future individual behavior of saltwater recreational fishing participation.

2. MARKET SEGMENTATION AND NEURAL NETWORKS

Market segmentation is a widely accepted concept in marketing research and planning, which is of dividing the heterogeneous market into some homogeneous groups of consumers who have common needs and wants (Myers, 1996). Weinstein (2004) provided the following definition: "*Segmentation marketing means knowing your customers, giving them exactly what they want or may want, building strong relationships with channel affiliates and co-marketing partners, and communicating via highly targeted promotional media.*"

A customer's response is influenced by a number of factors, such as his/her demographics, socio-economic status, geographic location, and more importantly, attitude and emotions at any given time. Most multivariate analytical techniques can be used in some way to create post hoc market segments. Moreover, neural networks are useful in a broad spectrum of ways, but one of the most popular applications is to the marketing world. Neural networks can be essential in market segmentation because many of them are adopted at the practice of classifying or grouping customers into identifiable groups according to customer characteristics.

Neural networks are one of the most popular machine learning methods which are able to do classification, clustering and prediction tasks. Multilayer perceptron (MLP) consists of multiple layers of working units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. MLP consists of three layers of nodes: an input layer, a hidden layer and an output layer. In the theoretical manner, MLP is universal approximator, and with respect to its inherent nature, it has a tremendous capacity of constructing any nonlinear mapping to any extent of accuracy (Hornik, Stinchcombe, & White, 1989). It does not need a priori model to be assumed or a priori assumptions to be made on the properties of data (Bishop, 2006).

Gardner and Dorling (1998) define multilayer perceptron as: "*a system of simple interconnected neurons, or nodes, which is a model representing a nonlinear mapping between an input vector and an output vector*". Thus, MLP is the most popular neural network method that has been widely used for many practical applications, and one good reason is that able to learn non-linear representations. It has been widely employed for modeling, prediction, classification, clustering, and optimization purposes (Ahmed, 2005; Bose, 2007; Costea & Nastac, 2005; De Gooijer & Hyndman, 2006; Do, Taherifar, & Vu, 2019; Ramchoun, Idrissi, Ghanou, & Ettaouil, 2017; Zacharis, 2016).

MLP is the most utilized model in neural network applications using the back-propagation training algorithm for multilayer feed-forward networks. MLP consists of perceptrons that are organized in layers: an input layer, one or more hidden layers, and the output layer. Each perceptron calculates the sum of the weighted inputs, and feeds it into its activation function. The result is then passed on to the next layer. The output layer has the same number of perceptrons as there are classes, and the perceptron with the highest activation will be consider the classification of the input sample. Training is achieved by successively feeding all training samples into the network, and comparing the output with the true class label (Haykin, 2009).

3. MATERIALS AND METHODS

The data used in this study was extracted from the database collected from the 2013 National Saltwater Angler Survey (Brinson & Wallmo, 2013) which was developed by the NOAA Fisheries and collected by the CIC Research. The survey targeted on saltwater anglers, above 16 years of age who had been saltwater fishing at least once in their life, to elicit their participation, fishing preferences and attitudes. The survey was implemented in six regions, including North Atlantic, Mid-Atlantic, South Atlantic, Gulf of Mexico, West Coast, and Alaska, in the U.S.

Respondents were asked, "On most of your fishing trips, how important is it to ---", to indicate 15 statements regarding the importance of fishing trips, using a Likert-type scale that ranged from 1 (Not important at all) through 5 (Extremely important). This study examined the psychometric properties of recreational fishing motivations from the 7,812 saltwater anglers who provided complete information for all 15 statements (Table 1).

The market segmentation techniques used in this study were: factor analysis for data preparation, cluster analysis for data examination, and discriminant analysis for classification. First, the dimensionality of the 15-item recreational fishing motivation scale was assessed by examining the factor solution (Gerbing & Anderson, 1988). Specifically, the amount of variance explained by the extracted factors (i.e., their eigenvalues) was noted. In addition, item-factor correlations (i.e., factor loadings) and other indices of model adequacy were examined. A principal component analysis was used to determine the factors identified to the sample. Second, a K-means cluster analysis was conducted to identify respondent groups exhibiting common patterns of responses. Third, a multilayer perceptron neural network model was employed as a predictive model in deciding the classification of saltwater anglers based on recreational fishing motivations.

Table 1. Descriptive statistics of recreational fishing motivations.

On most of your fishing trips, how important is it to ---	Mean	S.D.	Communalities
Catch fish	4.14	0.859	0.506
Catch as many fish as I can for consumption	2.99	1.290	0.706
Catch-and-release as many fish as possible	3.15	1.217	0.668
Catch a trophy-sized fish	3.04	1.290	0.642
Target a particular species	3.33	1.188	0.521
Catch the bag limit of a species I am targeting	2.77	1.302	0.700
Know that I will encounter abundant fish	3.64	1.066	0.578
Fish in an area that is not heavily congested	4.00	0.886	0.543
Be close to amenities	2.95	1.295	0.574
See information concerning fishing regulations clearly posted	3.62	1.274	0.681
Have access to staff to answer questions or provide information	2.78	1.273	0.747
Have easy access to weather and tide information	3.99	1.113	0.401
Fish in a scenic area	3.28	1.153	0.517
Fish with family or friends	4.33	0.843	0.717
Teach others about fishing	3.75	1.067	0.704

Note: Extremely important = 5, Somewhat important = 4, Neutral = 3, Somewhat unimportant = 2, Not important at all = 1.

4. RESULTS

4.1. Factor Analysis

The original 15-item recreational fishing motivation scale was factor analyzed with varimax rotation, which is an orthogonal rotation method that minimizes the number of variables that have high loadings on each factor, providing a clearer separation of the factors. As a result of the exploratory factor analysis, five factors were identified. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy, a measure of how suited your data is for each variable in the model and for the complete model for factor analysis, was 0.747, which meet the fundamental requirements for factor analysis. The Bartlett's test of Sphericity showed that nonzero correlations exist at the significance level of 0.001 (Table 2).

Each factor was named by examining the content of the variable making the greatest contribution to each of the dimensions. An initial interpretation of these factors suggested that Factor 1 named *Catch* factor comprised five items (structure coefficients ranging from 0.800 to 0.588) and explained 17.297 percent of the variance with an eigenvalue of 2.595. Factor 2 emphasized *Information* factor comprised four items (structure coefficients ranging from 0.853 to 0.511) and explained 15.420 percent of the variance with an eigenvalue of 2.313.

Factor 3 focused on *Site Preferences* factor comprised only two items (structure coefficients ranging from 0.716 to 0.660) and explained 9.587 percent of the variance with an eigenvalue of 1.438. Factor 4 focused on *Social* factor comprised two items (structure coefficients ranging from 0.790 to 0.770) and explained 9.571 percent of the variance with an eigenvalue of 1.436. Factor 5 focused on *Management* factor comprised two items as well (structure coefficients ranging from 0.771 to 0.665) and explained 9.483 percent of the variance with an eigenvalue of 1.423.

The Cronbach (1951) is the most widely used measure of reliability which is an assessment of the degree of consistency between multiple measurements of a variable. The internal consistency coefficient score of the 15-item recreational fishing motivation scale showed the Cronbach's alpha of 0.734 was acceptable, which explained a cumulative 61.358 percent of the variance in statement response (Table 2).

Table 2. Factor analysis of recreational fishing motivations.

On most of your fishing trips, how important is it to ---	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Factor 1: Catch					
Catch the bag limit of a species I am targeting	0.800				
Catch as many fish as I can for consumption	0.730				
Catch fish	0.634				
Target a particular species	0.618				
Know that I will encounter abundant fish	0.588				
Factor 2: Information					
Have access to staff to answer questions or provide information		0.853			
See information concerning fishing regulations clearly posted		0.814			
Be close to amenities		0.718			
Have easy access to weather and tide information		0.511			
Factor 3: Site Preferences					
Fish in an area that is not heavily congested			0.716		
Fish in a scenic area			0.660		
Factor 4: Social					
Fish with family or friends				0.790	
Teach others about fishing				0.770	
Factor 5: Management					
Catch-and-release as many fish as possible					0.771
Catch a trophy-sized fish					0.665
Eigenvalue	2.595	2.313	1.438	1.436	1.423
% of variance	17.297	15.420	9.587	9.571	9.483
Cumulative %	17.297	32.717	42.304	51.875	61.358
Reliability Alpha Coefficient of All 15 Items = 0.734					
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy = 0.747					
Bartlett's Test of Sphericity: Approx. Chi-Square = 25225.098; *df* = 105; $p < 0.001$					

4.2. Cluster Analysis

Cluster analysis techniques assign objects to groups so that there is as much similarity within groups, and difference between groups, as possible (Churchill & Iacobucci, 2005). Factor scores of recreational fishing motivation dimensions were used to cluster saltwater anglers. The K-means clustering method was used to identify a solution with the specified number of clusters. Consequently, a three-cluster solution was agreed upon the distance, computed using simple Euclidean distance, from the cluster centers to every object with the shortest distance to the cluster center. The clusters were labeled as *Catch and Social*, *Site Choice*, and *Fishing Related* clusters (Table 3).

The *Catch and Social* cluster: this was the largest group comprising of approximately 42.5 percent of the respondents. These respondents were positively connected with *Catch* and *Social*, but negatively identified with *Information*, *Site Preferences* and *Management*. The *Site Choice* cluster: with 33.9 percent of the respondents, this group was named after the positively strong association with *Information*, *Site Preferences*, *Social* and *Management*, but negatively identified with *Catch*. The *Fishing Related* cluster: this was the smallest group, comprising of approximately 23.6 percent of the respondents, named because of the positive factor score associated with *Management*, negatively identified with *Catch*, *Information*, *Site Preferences* and *Social* among these respondents.

Table 3. Cluster analysis of saltwater recreational anglers.

Factor	Catch and Social	Site Choice	Fishing Related
Catch	0.7493	-0.9252	-0.0188
Information	-0.0965	0.1130	-0.0068
Site Preferences	-0.0448	0.3144	-0.3707
Social	0.3853	0.3612	-1.2108
Management	-0.2277	0.0571	0.3272
n = 7.812	3317	2649	1846
Percentage	42.5	33.9	23.6

4.3. Discriminant Analysis

Discriminant analysis is a statistical technique to classify the target population into the specific categories or groups based on the certain attributes (predictor variables or independent variables) (Fisher, 1936; Tabatchnich & Fidell, 2013). Results of the cluster analysis were tested for accuracy using the linear discriminant analysis employed as a useful complement to cluster analysis, which is used primarily to predict membership in two or more mutually exclusive groups. In this case, the Wilk's Lambda scores were 0.200 (χ^2 = 12582.739; df = 10; p < 0.001) and 0.471 (χ^2 = 5877.154; df = 4; p < 0.001) for both discriminant functions, respectively, indicating that group means were significantly different. The canonical correlation results were both above 0.7, supporting that there were strong relationships between the discriminant score and the cluster membership.

Table 4. Classification results[a] based on discriminant analysis.

Factor		Cluster	Predicted Group Membership			
			Catch and Social	Site Choice	Fishing Related	Total
Original	Count	Catch and Social	3265	34	18	3317
		Site Choice	42	2593	14	2649
		Fishing Related	32	12	1802	1846
	%	Catch and Social	98.5	1.0	0.5	100
		Site Choice	1.6	97.9	0.5	100
		Fishing Related	1.7	0.7	97.6	100

Note: a. 98.1% of original grouped cases correctly classified.

The classification results based on discriminant analysis (Table 4), 3317 cases fell into the *Catch and Social* cluster, 2649 fell into the *Site Choice* cluster, and 1846 fell into the *Fishing Related* cluster in the original row total. Across the row, there were 3265 predicted correctly and 52 predicted incorrectly (34 predicted in the *Site Choice* cluster and 18 predicted in the *Fishing Related* cluster) in the *Catch and Social* cluster. Similarly, across the column, there were 3265 predicted correctly and 74 predicted incorrectly (42 predicted in the *Site Choice* cluster and 32 predicted in the *Fishing Related* cluster) in the *Catch and Social* cluster (Table 4).

4.4. Multilayer Perceptron (MLP) Neural Network Analysis

After the formation of the three identified saltwater angler groups, a MLP neural network model was employed as a predictive model in deciding the classification of saltwater anglers based on recreational fishing motivations. The MLP Module of IBM SPSS Statistics 26 was used as the tool to build the neural network model and to test its accuracy. The MLP neural network model, trained with a back-propagation learning algorithm which uses the gradient descent to update the weights towards minimizing the error function.

The aim of this analysis was to examine whether a MLP neural network model can help saltwater recreational fisheries managers to correctly recognize the importance of fishing trips, by analyzing data obtained from the saltwater anglers. The data were randomly assigned to training (n = 5451, 69.8%) and testing (n = 2361, 30.2%) subsets. The training dataset was used to find the weights and to build the neural network model, while the testing data was used to find errors and to prevent overtraining during the training mode.

In order to find the best MLP neural network, disparate possible networks were tested and it concluded that the MLP neural network with a single hidden layer was the best option for this study. Sheela and Deepa (2013) pointed out that as the number of neurons or the number of layers of a neural network increase, the training error also increases due to the overfitting. It is clear that using a single input layer, a single hidden layer, and a single output layer in the neural network will help to decrease the probability of overfitting and will require relatively lower computational time.

One of the most salient considerations in the construction of neural network is choosing activation functions for hidden and output layers that are differentiable. The results showed that in this study, the hyperbolic tangent activation function can be used for the single hidden layer because it cannot be used in networks with many layers due to the vanishing gradient problem, and the rectified linear activation function can be used for the output layer not only because it overcomes the vanishing gradient problem, but also allows models to learn faster and perform better (Goodfellow, Bengio, & Courvelle, 2016).

The MLP Module of IBM SPSS Statistics 26 was used as the tool to choose the best architecture model automatically and it built the network with one hidden layer. From the fifteen independent variables in the input layer, the architecture automatically selected 9 nodes in the hidden layer, and the output layer had 3 nodes as the dependent variable named *Cluster*. The hyperbolic tangent was used as the activation function in the hidden layer, while the softmax function was used as the activation function in the output layer. Cross-entropy was used as error function because of the use of softmax function. Intuitively, the cross-entropy loss function is used to measure the error at a softmax layer, typically the final output layer in a neural network.

The network diagram showed the 15 input nodes, the 9 hidden nodes and the three output nodes representing the three identified saltwater angler categories. In the architectural point of view, it was a 15-9-3 neural network, means that there were total 15 independent (input) variables, 9 neurons in the hidden layer and 3 dependent (output) variables (Figure 1).

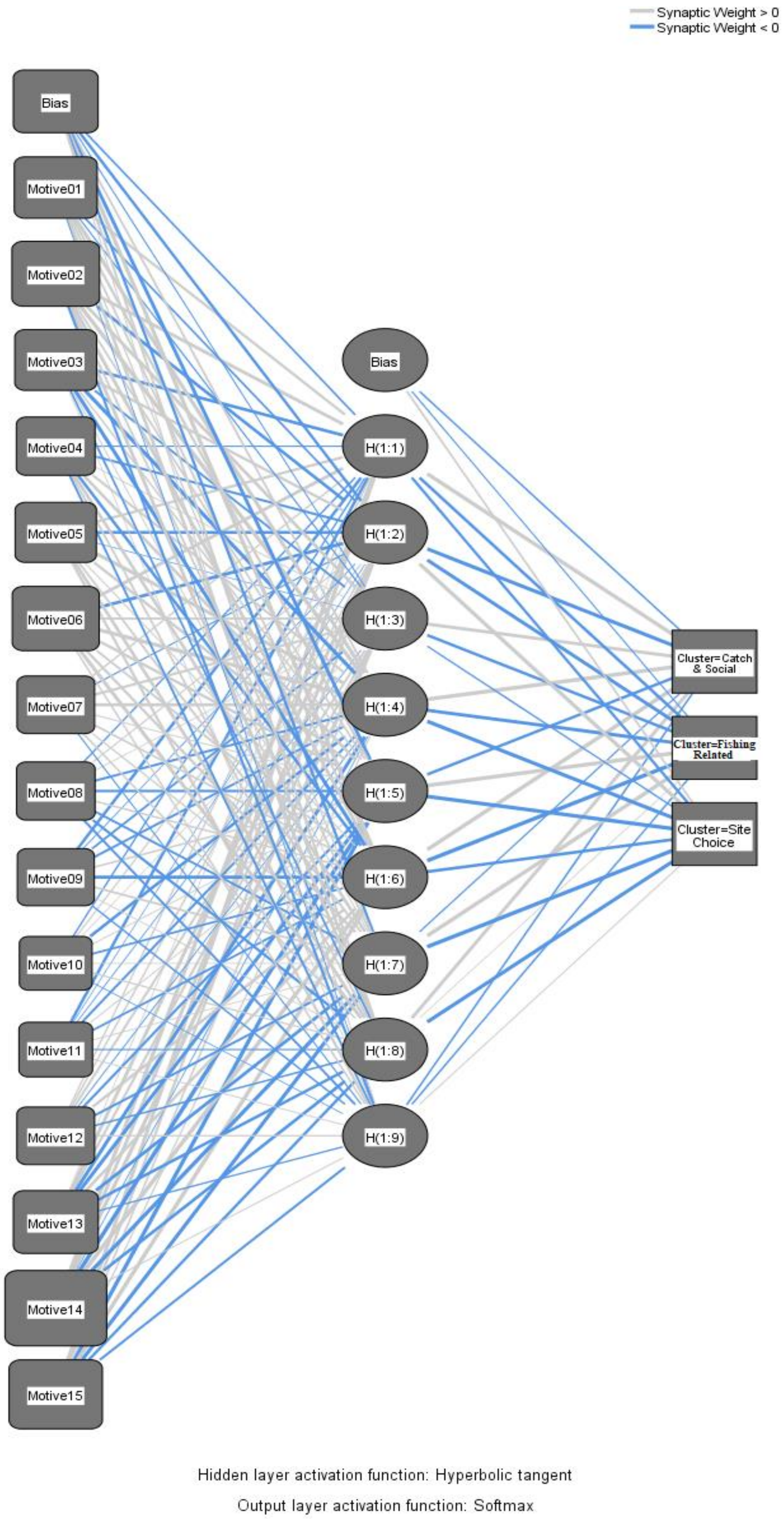

Figure 1. Network diagram.

The model summary provided information related to the results of training and testing sample (Table 5). Cross-entropy error is displayed because the analysis is based on softmax activation function, and is given for both training and testing sample since is the error function that neural network minimizes during the training phase. The value of cross-entropy error (= 132.610) indicated the power of the model to predict the three identified angler groups. The cross-entropy error was less for the testing sample compared with the training data set, meaning that the neural network model had not been overfitted to the training data.

In this study, the percentage of incorrect prediction was equal to 0.6% in the training sample. So the percentage of correct prediction was 99.4% which is an excellent prediction in a qualitative study for determining management results of recognizing the importance of fishing trips. The learning procedure was performed until 1 consecutive step with no decrease in error function was attained from the training sample (Table 5).

Table 5. Model summary.

Target	Type of neural network trained	Stopping rule that stopped training
Training	Cross Entropy Error	132.610
	Percent Incorrect Predictions	0.6%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.98
Testing	Cross Entropy Error	74.052
	Percent Incorrect Predictions	0.9%

Note: Dependent Variable: Cluster.
a. Error computations are based on the testing sample.

Based on the MLP neural network, a predictive model was developed and displayed a classification table (i.e. confusion matrix) for categorical dependent variable, the three identified saltwater angler groups, by partition and overall (Table 6). As can be seen, the MLP neural network correctly classified 5418 saltwater anglers out of 5451 in the training sample and 2340 out of 2361 in the testing sample. Overall 99.4% of the training cases were correctly classified. The predictive model developed had excellent classification accuracy.

Using the training sample only, it was able to classify 2275 *Catch and Social* saltwater anglers into the *Catch and Social* group, out of 2290. It held 99.3% classification accuracy for the *Catch and Social* group. Similarly, the same model was able to classify 1297 *Fishing Related* saltwater anglers into the *Fishing Related* group out of 1306, and 1846 *Site Choice* saltwater anglers into the *Site Choice* group out of 1858. It was able to generate 99.5% and 99.4% classification accuracy for the *Fishing Related* and *Site Choice* groups, respectively (Table 6).

Table 6. Predictive ability and classification results.

Classification					
Sample	Observed	Predicted			
		Catch and Social	Fishing Related	Site Choice	Percent Correct
Training	Catch and Social	2275	11	4	99.3%
	Fishing Related	4	1297	2	99.5%
	Site Choice	8	4	1846	99.4%
	Overall Percent	42.0%	24.1%	34.0%	99.4%
Testing	Catch and Social	1019	4	4	99.2%
	Fishing Related	6	536	1	98.7%
	Site Choice	2	4	785	99.2%
	Overall Percent	43.5%	23.0%	33.5%	99.1%

Note: Dependent Variable: Cluster.

The importance of the individual independent variables (factor influencing recreational fishing motivations) is a measure of how much the neural network model predicted value changes for different independent variables. The input parameters -- recreational fishing motivations, which influenced the three identified saltwater angler groups have been ranked by the neural network model were given in the following Table 7. Hence, Independent variable importance analysis provides the sensitivity analysis, by computing the importance of each independent variable, which in turn determines the structure of the neural network.

The first three significant dominant factors that were "Fish with family or friends" (100%), contributed the most in the neural network model construction, followed by "Teach others about fishing" (75.1%), and "Catch as many fish as I can for consumption" (58.4%), had the greatest effect on how the recreational anglers' motivations, in terms of the importance of fishing trips. The next two important factors were "Catch the bag limit of a species I am targeting" (56.2%) and "Fish in a scenic area" (50.3%). The other factors were relatively not important such as "Know that I will encounter abundant fish" (28.7%), "Be close to amenities" (26.8%), "Have access to staff to answer questions or provide information" (17.0%), and the least important factor which has been identified was "See information concerning fishing regulations clearly posted" (14.0%).

Table 7. Independent variable importance analysis.

On most of your fishing trips, how important is it to ---	Importance	Normalized Importance	Rank
Catch fish	0.069	44.3%	6
Catch as many fish as I can for consumption	0.091	58.4%	3
Catch-and-release as many fish as possible	0.065	41.7%	7
Catch a trophy-sized fish	0.050	32.0%	9
Target a particular species	0.061	39.5%	8
Catch the bag limit of a species I am targeting	0.087	56.2%	4
Know that I will encounter abundant fish	0.045	28.7%	12
Fish in an area that is not heavily congested	0.049	31.5%	10
Be close to amenities	0.042	26.8%	13
See information concerning fishing regulations clearly posted	0.022	14.0%	15
Have access to staff to answer questions or provide information	0.026	17.0%	14
Have easy access to weather and tide information	0.046	29.5%	11
Fish in a scenic area	0.078	50.3%	5
Fish with family or friends	0.155	100.0%	1
Teach others about fishing	0.116	75.1%	2

5. DISCUSSION AND CONCLUSIONS

Identification of saltwater angler motivations for fishing is important because it helps saltwater recreational fisheries managers understand why people fish and why they choose a particular environment to fish. By identifying saltwater angler motivations, saltwater recreational fisheries managers can better understand the experiences desired by saltwater anglers.

This study suggests that the saltwater anglers' motivations – the importance of fishing trips – may be important in distinguishing different segments within the angling population. This study suggested that the 15 statements regarding the importance of fishing trips of U.S. saltwater anglers could be condensed into five attitudinal dimensions (*Catch*, *Information*, *Site Preferences*, *Social*, *Management*) using principal components analysis and performed a three-cluster solution, including *Catch and Social*, *Site Choice*, and *Fishing Related* groups, using two-stage cluster analysis.

The *Catch and Social* angler cluster was the most common cluster of U.S. saltwater anglers, comprising 42.5% of the survey sample. They were more likely than their counterparts in the *Site Choice* and *Fishing Related* angler clusters to view the experiential and social components of their fishing experience as very or extremely important. In contrast, they placed less importance on information, site preferences, and other more traditional aspects of saltwater recreational fisheries management.

The customary objectives of saltwater recreational fisheries managers, fish size and populations, are not the primary attractants for all anglers. Indeed, *Site Choice* angler cluster, who comprised about 34% of the sample, place a relatively low priority on catching fish. To appeal to this segment, saltwater recreational fisheries managers should work to enhance the perceived environmental quality of fishing sites and to provide facilities and information that enhance the convenience and relaxation of the angling experience.

At the same time, the traditional saltwater recreational fisheries management goals are justified by their importance to the *Management* angler cluster. They are more likely to make a significant contribution to fish size and populations in which their angling activity takes place. To retain this important angler group, saltwater recreational fisheries managers should continue to pursue the traditional saltwater recreational fisheries management goals that enhance catch success.

The primary reasons for fishing for all saltwater anglers are to relax and enjoy the outdoors. Catching fish to eat or catching trophy fish are less important overall, but, to certain segments of anglers, these are very important reasons for fishing. Developing saltwater fisheries in natural settings, reducing crowding, and reducing user conflict will help the saltwater recreational fisheries managers provide fishing opportunities in which saltwater anglers can enjoy the outdoors and relax. Subgroups of saltwater anglers do place a great deal of importance on the catch aspects of fishing. Recognition of those subgroups and providing the experiences that they desire (trophy fish and consuming fish) should help improve saltwater angler satisfaction.

The MLP neural network is widely considered as an efficient approach to adaptively classify patterns. In this work, an attempt was made to improve the learning capabilities of a MLP neural network and reduced the amount of time and resource required by the learning process by sampling the input dataset to be learnt using the K-means algorithm. The multilayer perceptron neural network model was utilized as a predictive model in deciding the classification of saltwater anglers based on recreational fishing motivations. From an architectural perspective, it showed a 15-9-3 neural network. The results also revealed that social activities and catch consideration were the greatest effect on how the saltwater anglers' perceives in terms of the importance of fishing trips.

Without information to identify saltwater angler motivations that influence saltwater recreational fishing participation among different angler segments, it is difficult to successfully attract diverse angler markets associated with their motivations and interests. Therefore, the success of the saltwater recreational fisheries programs and management strategies should consider the information of understanding saltwater angler motivations. Saltwater recreational fisheries managers should address the desires and needs of each segment when developing saltwater recreational fisheries management plans.

These results illustrate the diversity of saltwater anglers' motivations and belie the concept of an "average" angler. Saltwater recreational fisheries managers should be aware of this diversity when considering management options and striving to serve the entire angling public. There is room for expansion into several different markets. By providing opportunities for each segment, saltwater recreational fisheries management should be more effective and saltwater angler satisfaction and participation may increase. However saltwater recreational fisheries managers should be aware that providing the desired experiences of one segment may come at the expense of other segments. If possible, saltwater recreational fisheries managers should find a balance of opportunities for each segment and be careful not to exclude segments of saltwater anglers.

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