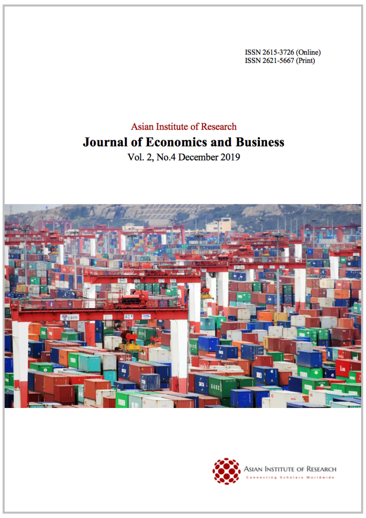

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Clustering Neural Network Analysis of Recreational Fisheries Management Strategies

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Abstract
This study utilized data extracted from the 2013 National Saltwater Angler Survey to understand saltwater recreational anglers' preferences toward recreational fisheries management strategies, to identify groups exhibiting common patterns of responses, and to examine the association between socio-demographic characteristics and the groups identified. Saltwater recreational anglers' preferences toward recreational fisheries management strategies were examined through factor analysis which identified four reliable factors. Cluster analysis was employed to identify three prominent recreational angler groups. Statistical tests were employed to investigate the association between socio-demographic characteristics, including age, gender, income level, educational level, region of the respondent, and the identified recreational angler groups. The multilayer perceptron neural network model was utilized as a predictive model in deciding recreational anglers' preferences toward recreational fishing management strategies. From an architectural perspective, it showed a 15-7-3 neural network construction. The results also revealed that fisheries habitat development and bag limit consideration were the greatest effect on how the recreational anglers' preferences in terms of recreational fisheries management strategies. Results of this study may provide insight regarding the preferences toward recreational fisheries management strategies from saltwater recreational anglers as an indicator of potential participation and behavior of saltwater recreational fisheries management.

Keywords: Saltwater, Recreational Anglers, Preferences, Recreational Fisheries Management Strategies, Factor Analysis, Cluster Analysis, Discriminant Analysis, Multilayer Perceptron, Neural Network

1. Introduction

The National Oceanic and Atmospheric Administration (NOAA) is responsible for the management, conservation, and protection of living marine resources within the United States. *A Vision for Managing America's Saltwater Recreational Fisheries* (The Commission on Saltwater Recreational Fisheries Management, 2014) outlined a new paradigm for conserving marine fishing resources while producing the full range of saltwater recreational fishing's economic, social, and conservation benefits.

In 2011, approximately 11 million Americans saltwater fished recreationally, spending $27 billion in pursuit of their sport. That activity generated more than $70 billion in economic output and sustained 450,000 jobs. Anglers also contributed more than $1.5 billion annually to fisheries habitat and conservation via excise taxes and license fees alone (The Commission on Saltwater Recreational Fisheries Management, 2014). From 2006 to

2015, the total number of anglers has decreased by 33.1%. The number of angler trips also decreased by 27% during that same time period (National Marine Fisheries Service, 2017). Although these decreases may reflect recessionary economic conditions, recreational fisheries management strategies are in need of an update and may benefit from placing more emphasis on recreational fishing on a federal level.

The primary law governing marine fisheries management in the United States, known as the Magnuson-Stevens Act, has never properly addressed the importance of recreational fishing and this has led to shortened or even cancelled seasons, reduced bag limits, and unnecessarily imposed restrictions. Recreational fishing in the United States has decreased significantly over the last decade. Increasingly aware of how important and integral recreational fishing is to the nation's commerce, NOAA has decided to create the U.S. National Saltwater Recreational Fisheries Policy to make this a "key focus of Agency action." Its major goals include: Support and maintain sustainable saltwater recreational fisheries resources, including healthy marine and estuarine habitats; Promote saltwater recreational fishing for the social, cultural, and economic benefit of the nation; Enable enduring participation in, and Enjoyment of, saltwater recreational fisheries through science-based conservation and management (National Marine Fisheries Service, 2015).

On April 6, 2017, the Modernizing Recreational Fisheries Management Act was introduced in the House of Representatives as HR 2023. It is designed to address federal saltwater management issues by adapting the federal system that has historically focused on commercial fishing to now meet the needs of the nation's saltwater anglers (National Marine Fisheries Service, 2017). Regardless of which recreational fisheries management strategies are implemented, understanding the preferences of the recreational anglers themselves when planning such strategy should increase the likelihood for successful implementation (Ihde et al., 2010). The key to the sustainability of recreational fisheries is good governance, which is transparent and provides for the stakeholders to feel adequately represented (Hilborn, 2007).

The main purpose of this paper was to explore segmentation of the recreational angler population based on certain preferences of interest regarding recreational fisheries management strategies using psychometric data, while also estimating the size of recreational angler subgroups that have been identified, which may be useful for saltwater recreational fisheries managers to prioritize and effectively allocate fisheries management initiatives and resources. Neural networks have been used in fisheries related research in forecasting, classification, distribution, and fisheries management since 1978 (Suryanarayana et al., 2008). Very few detailed studies have been carried out on understanding how saltwater recreational anglers perceive recreational fishing management strategies and specifically on the classification of this interest group of recreational anglers by using the statistical model identification based clustering neural network approach.

2. Clustering Neural Networks

Clustering using neural networks has recently demonstrated promising performance in machine learning and computer vision applications. It is widely used for pattern recognition, feature extraction, image segmentation, function approximation, and data mining. Clustering is a fundamental data analysis method, can be based on statistical model identification or competitive learning. Clustering of data is also a method, most commonly referred to as unsupervised learning technique as the grouping is based on a natural or inherent characteristic, by which large sets of data are grouped into clusters of smaller sets of similar data.

As an unsupervised classification technique, clustering identifies some inherent structures present in a set of objects based on a similarity measure. It is primarily concerned with distance measures and clustering algorithms which calculate the difference between data and divide them systematically. The K-means clustering algorithm (Forgy, 1965; MacQueen, 1967) is one of the simplest unsupervised learning algorithms that solves the well-known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters fixed a priori.

On the other hand, classification, also known as supervised learning technique wherein machines learn from already labeled or classified data, is a process related to categorization, the process in which ideas and objects are recognized, differentiated and understood. It is highly applicable in pattern recognition, statistics, and biometrics. Classification seeks to determine which explicit group a certain object belongs to, while clustering organizes objects with the aim to narrow down relations as well as learn novel information from hidden patterns.

Neural networks have emerged as an important tool for classification. A neural network is a mathematical procedure which is optimized, or taught, to produce some sort of output which is desired. This can be used for anything which needs to make some sort of prediction based on evidence which takes the same form of representation consistently. Neural networks are well suited to model complex relationships between inputs and outputs or to find patterns in data. Moreover, neural networks are used for clustering through unsupervised learning, which means you can group categorize labeled data.

The purpose of a neural network is to learn to recognize patterns in your data. Once the neural network has been trained on samples of your data, it can make predictions by detecting similar patterns in future data. The behavior of the neural network depends on the relationships and connections among individual components of the network. A neural network is a multilayer perceptron with simple connections between different components, is especially suitable for classification and is widely used in practice. In each layer, one or more processing unit(s) called artificial neurons or nodes are present which perform a simplified version of what human brain's neurons do (Manel et al., 1999). 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”.

There are three main neural layers in each neural network: The first layer which is called the input layer is where the data enters the network and is then transferred to the processors. The second layer is called hidden layer. This layer functions by receiving the inputs from the input layer and by considering the weights of the relationships among different input units and hidden units. These weights determine when the hidden layer should be activated. The last layer is called the output layer. The functionality of this layer depends upon the activities of hidden layer and the weights between hidden units and output units. Multilayer perceptron uses backpropagation to classify instances, which is one of the most widely used neural network techniques in data analysis (Rumelhart, Hinton, and Williams, 1986; Chauvin and Rumelhart, 1995).

3. Materials and Methods

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

Respondents were asked, “Please state your preference for using each strategy listed below,” to indicate 15 statements regarding optional recreational fisheries management strategies, using a Likert-type scale that ranged from 1 (do not prefer at all) through 4 (strongly prefer), and 5 (I am unsure). This study examined the psychometric properties of recreational fisheries management strategies from the 7764 saltwater anglers who provided complete information for all 15 optional statements (Table 1).

First, the dimensionality of the 15-item recreational fisheries management strategies was assessed by examining the factor solution (Gerbing and 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 in this study. Second, a K-means cluster analysis was conducted to identify respondent groups exhibiting common patterns of responses. Third, a series of statistical tests was utilized to examine the association between socio-demographic characteristics and the identified clusters. Fourth, a multilayer perceptron neural network model was employed as a predictive model in deciding the saltwater anglers' preferences toward recreational fishing management strategies.

Table 1: Descriptive Statistics of Recreational Fisheries Management Strategies

Strategy	Please state your preference for using each strategy listed below	Mean	S.D.	Communalities
Strategy01	Establish minimum size limits of the fish you can keep	3.32	0.92	0.637
Strategy02	Establish minimum size limits of the fish you can keep	2.72	1.26	0.545
Strategy03	Limit the total number of fish you can keep	3.12	1.02	0.593
Strategy04	Manage some species as catch-and-release only	2.75	1.24	0.486
Strategy05	Establish longer seasons with more restrictive bag limits	2.59	1.31	0.375
Strategy06	Establish shorter seasons with less restrictive bag limits	2.02	1.38	0.705
Strategy07	Establish shorter seasons with a larger variety of species you can legally catch	2.25	1.41	0.673
Strategy08	Increase the recreational harvest limit by decreasing the commercial harvest limit	3.05	1.27	0.525
Strategy09	Divide the recreational harvest limit among different modes (e.g. private anglers and for-hire/charter boat anglers)	2.64	1.38	0.368
Strategy10	Restrict certain types of fishing gear	2.74	1.35	0.330
Strategy11	Require the use of release techniques that reduce fish mortality	3.20	1.08	0.451
Strategy12	Provide artificial fish habitat (e.g. artificial reef) in some areas of the ocean	3.43	0.95	0.513
Strategy13	Protect and restore fish habitat that has been degraded	3.61	0.72	0.505
Strategy14	Designate some areas of the ocean as marine reserves with catch-and-release fishing only	2.99	1.23	0.724
Strategy15	Close some areas of the ocean for certain seasons	2.77	1.37	0.674

(Strongly prefer = 4, Somewhat prefer = 3, Slightly prefer = 2, Do not prefer at all = 1, I am unsure = 5)

4. Results

4.1 Factor Analysis

Factor analysis uses mathematical procedures for the simplification of interrelated measures to discover patterns in a set of variables (Child, 2006). In this study, the original 15-item recreational fisheries management strategies was factor analyzed with varimax rotation, providing a clearer separation of the factors. As a result of the exploratory factor analysis, four factors were identified. The KMO measure of sampling adequacy was 0.821, which met the fundamental requirements for factor analysis. The Bartlett's test of Sphericity showed that nonzero correlations existed at the significance level of 0.001 (Table 2).

The Cronbach's alpha, developed by Lee J. Cronbach in 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 fisheries management strategies showed the Cronbach's alpha of 0.793, which was acceptable. Each of these four factors had a satisfactory Cronbach's alpha of 0.696, 0.637, 0.659, and 0.716, respectively, which explained a cumulative 54.025 percent of the variance in statement response (Table 2).

Table 2: Factor Analysis of Recreational Fisheries Management Strategies

Please state your preference for using each strategy listed below	*Keep Limits*	*Catch Limits*	*Season Limits*	*Zone Limits*
Establish minimum size limits of the fish you can keep	0.779			
Establish maximum size limits of the fish you can keep	0.710			
Limit the total number of fish you can keep	0.742			
Manage some species as catch-and-release only	0.495			
Establish longer seasons with more restrictive bag limits			0.481	
Establish shorter seasons with less restrictive bag limits			0.835	

Establish shorter seasons with a larger variety of species you can legally catch			0.809	
Increase the recreational harvest limit by decreasing the commercial harvest limit		0.628		
Divide the recreational harvest limit among different modes		0.462		
Restrict certain types of fishing gear		0.431		
Require the use of release techniques that reduce fish mortality		0.521		
Provide artificial fish habitat (e.g. artificial reef) in some areas of the ocean		0.696		
Protect and restore fish habitat that has been degraded		0.604		
Designate some areas of the ocean as marine reserves with catch-and-release fishing only				0.810
Close some areas of the ocean for certain seasons				0.783
Eigenvalue	2.198	2.046	1.939	1.920
% of variance	14.656	13.640	12.926	12.802
Cumulative %	14.656	28.297	41.223	54.025
Reliability Alpha Coefficient	0.696	0.637	0.659	0.716
Reliability Alpha Coefficient of All 15 Items = 0.793				
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy = 0.821				
Bartlett's Test of Sphericity: Approx. Chi-Square = 25364.604, $df = 105$, $p < 0.001$				

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 *Keep Limits* factor, comprised four items (structure coefficients ranging from 0.779 to 0.495) and explained 14.656 percent of the variance with an eigenvalue of 2.198. Factor 2, which emphasized *Catch Limits* factor, comprised six items (structure coefficients ranging from 0.696 to 0.431) and explained 13.640 percent of the variance with an eigenvalue of 2.046. Factor 3, which focused on *Season Limits* factor, comprised three items (structure coefficients ranging from 0.835 to 0.481) and explained 12.926 percent of the variance with an eigenvalue of 1.939. Factor 4 named on *Zone Limits* factor comprised only two items (structure coefficients ranging from 0.810 to 0.783) and explained 12.802 percent of the variance with an eigenvalue of 1.920 (Table2).

4.2 Cluster Analysis

Cluster analysis technique assigns objects to groups so that there is as much similarity within groups, and difference between groups, as possible (Churchill and Iacobucci, 2005). Factor scores of recreational fisheries management strategies dimensions were used to cluster recreational 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, which were labeled as *Zonal and Catch Restrictions*, *Keep and Catch Restrictions*, and *Seasonal Restrictions* clusters (Table 3).

The *Zonal and Catch Restrictions* cluster, with 29.0 percent of the respondents, was named after the positively strong association with *Zone Limits* and *Catch Limits*, but negatively identified with *Keep Limits* and *Season Limits*. Furthermore, the *Zonal and Catch Restrictions* cluster demonstrated more preference for prohibiting recreational fishing in certain geographic areas or zones and for fish population development.

The *Keep and Catch Restrictions* cluster was the largest group comprising of approximately 44.8 percent of the respondents. These respondents were positively associated with *Keep Limits* and *Catch Limits*, but negatively identified with *Season Limits* and *Zone Limits*. Furthermore, the *Keep and Catch Restrictions* cluster also demonstrated more preference for various restrictions related to fish caught and for fish population development.

The *Seasonal Restrictions* cluster was the smallest group, comprising of approximately 26.2 percent of the respondents, named because of the positive factor score associated with *Season Limits* and negatively identified with *Catch Limits*, *Zone Limits*, and *Keep Limits* among these respondents. Furthermore, the *Seasonal Restrictions* cluster demonstrated more preference for prohibiting recreational fishing during certain times of year or seasons.

Table 3: Cluster Analysis of Saltwater Recreational Anglers

	Zonal and Catch Restrictions	*Keep and Catch Restrictions*	*Seasonal Restrictions*
Keep Limits	-0.977	0.696	-0.109
Catch Limits	0.352	0.387	-1.052
Season Limits	-0.193	-0.209	0.571
Zone Limits	0.441	-0.012	-0.468
n = 7764	2252	3479	2033
Percentage	29.0	44.8	26.2

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; Tabatchnick and 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 0.193 ($\chi^2 = 12763.468$, $df = 8$, $p < 0.001$) and 0.471 ($\chi^2 = 5839.489$, $df = 3$, $p < 0.001$) 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).

Table 4: Canonical Correlation of Discriminant Functions

Function	Eigenvalue	% of Variance	Canonical Correlation
1	1.441*	56.2	0.768
2	1.122*	43.8	0.727

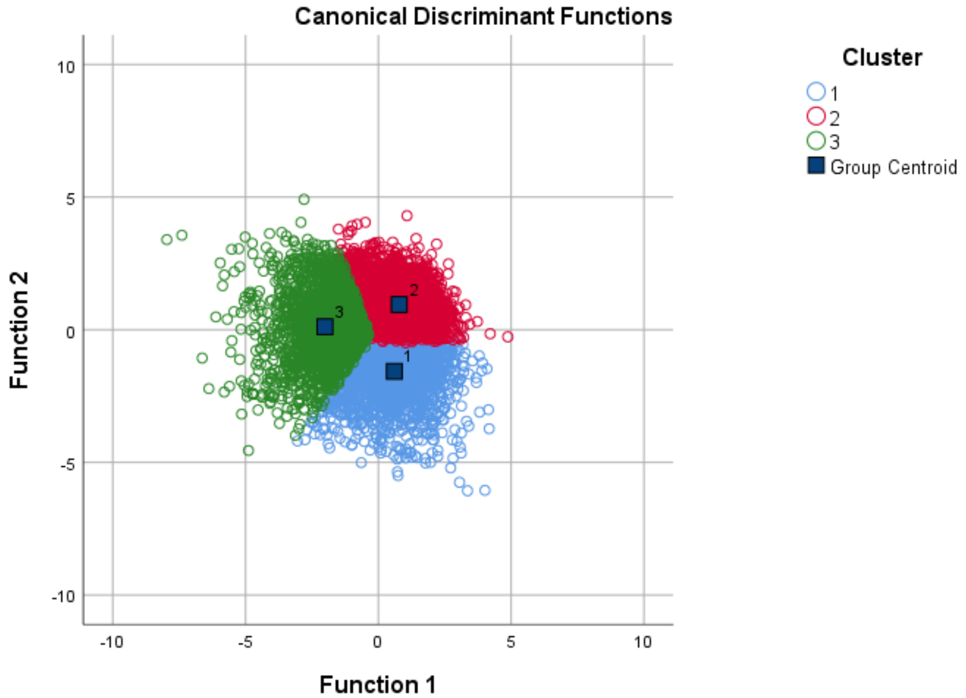
* First 2 canonical discriminant functions were used in the analysis.

Two discriminant functions were formulated (Table 5). The first function is a function for discriminating between *Zonal and Catch Restrictions*, *Keep and Catch Restrictions* and *Seasonal Restrictions* clusters combined, and the second function for discriminating between *Keep and Catch Restrictions* and *Seasonal Restrictions* clusters, respectively. The first function is the most powerful differentiating dimension, but the second function may also represent additional significant dimensions of differentiation. Though mathematically different, each discriminant function is a dimension which differentiates a case into categories of the dependent variable, the three identified recreational angler groups, based on its values on the independent variables. Furthermore, the territorial map is a tool for assessing discriminant analysis results by plotting the group membership of each case on a graph (Figure 1).

Table 5: Standardized Canonical Discriminant Function Coefficient

	Function 1	Function 2
Keep Limits	0.158	0.989
Catch Limits	0.992	-0.040
Season Limits	-0.650	0.028
Zone Limits	0.510	-0.391

Figure 1: Territorial Map



(1 = *Zonal and Catch Restrictions* cluster; 2 = *Keep and Catch Restrictions* cluster; 3 = *Seasonal Restrictions* cluster)

The classification results based on discriminant analysis (Table 6), 2252 cases fell into the *Zonal and Catch Restrictions* cluster, 3479 fell into the *Keep and Catch Restrictions* cluster, and 2033 fell into the *Seasonal Restrictions* cluster in the original row total, which is the frequencies of groups found in the data. Across each row, how many of the cases in the group can be classified by this analysis into each of the different groups. For example, of the 2252 cases that were in the *Zonal and Catch Restrictions* cluster, 2172 were predicted correctly and 80 were predicted incorrectly (61 were predicted to be in the *Keep and Catch Restrictions* cluster and 19 were predicted to be in the *Seasonal Restrictions* cluster).

Predicted group membership indicates the predicted frequencies of groups from the analysis. The numbers going down each column indicate how many were correctly and incorrectly classified. For example, of the 2200 cases that were predicted to be in the *Zonal and Catch Restrictions* cluster, 2172 were correctly predicted, and 28 were incorrectly predicted (20 cases were in the *Keep and Catch Restrictions* cluster and 8 cases were in the *Seasonal Restrictions* cluster) (Table 6).

Table 6: Classification Results[a] Based on Discriminant Analysis

			Predicted Group Membership			
		Cluster	Zonal & Catch	Keep & Catch	Seasonal	Total
Original	Count	Zonal & Catch	2172	61	19	2252
		Keep & Catch	20	3416	43	3479
		Seasonal	8	8	2017	2033
	%	Zonal & Catch	96.4	2.7	0.8	100
		Keep & Catch	0.6	98.2	1.2	100
		Seasonal	0.4	0.4	99.2	100

a. 98.0% of original grouped cases correctly classified
(Zonal & Catch = *Zonal and Catch Restrictions* cluster; Keep & Catch = *Keep and Catch Restrictions* cluster; Seasonal = *Seasonal Restrictions* cluster)

4.4 Statistical Tests

Using the Chi-square test, the three identified recreational angler groups demonstrated significant differences in gender composition ($\chi^2 = 11.251$, $df = 2$, $p = 0.004$) (Table 7), and in region composition ($\chi^2 = 61.582$, $df = 10$, $p = 0.000$) (Table 8). But there were no significant differences in income composition ($\chi^2 = 19.208$, $df = 14$, $p = 0.157$) (Table 9), and in education composition ($\chi^2 = 7.163$, $df = 8$, $p = 0.519$) (Table 10) among the three identified recreational angler groups, respectively.

Table 7: Gender Composition of the Saltwater Recreational Angler Clusters

Gender / Cluster	Zonal and Catch Restrictions	Keep and Catch Restrictions	Seasonal Restrictions	Total
Male	1840	2959	1720	6501
Female	412	520	331	1263
Total	2252	3479	2033	7764

Table 8: Region Composition of the Saltwater Recreational Angler Clusters

Region / Cluster	Zonal and Catch Restrictions	Keep and Catch Restrictions	Seasonal Restrictions	Total
Alaska	63	61	59	183
West Coast	294	511	372	1177
North Atlantic	285	468	329	1082
Mid-Atlantic	550	817	386	1753
South Atlantic	504	807	432	1743
Gulf of Mexico	556	815	455	1826
Total	2252	3479	2033	7764

Table 9: Income Composition of the Saltwater Recreational Angler Clusters

Income Level / Cluster	Zonal and Catch Restrictions	Keep and Catch Restrictions	Seasonal Restrictions	Total
Less than $20,000	139	210	137	486
$20,000-$39,999	307	417	292	1016
$40,000-$59,999	368	596	314	1278
$60,000-$79,999	352	572	322	1246
$80,000-$99,999	350	497	309	1156
$100,000-$149,999	433	651	384	1468
$150,000-$199,999	142	256	145	543
$200,000 or more	161	280	130	571
Total	2252	3479	2033	7764

Table 10: Education Composition of the Saltwater Recreational Angler Clusters

Educational Level / Cluster	Zonal and Catch Restrictions	Keep and Catch Restrictions	Seasonal Restrictions	Total
12th Grade or less	162	262	164	588
High school graduate or GED	536	797	506	1839
Associate or technical school degree or college coursework	691	1048	594	2333
Bachelor’s degree	495	811	469	1775
Advanced, professional, or doctoral degree or coursework	368	561	300	1229
Total	2252	3479	2033	7764

Table 11: Cluster Means of the Saltwater Recreational Angler Clusters

Dependent Variable	Zonal and Catch Restrictions		Keep and Catch Restrictions		Seasonal Restrictions		Total	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Years of Fishing	27.65	17.504	29.07	17.636	25.20	17.382	27.64	17.600
Age	52.44	13.832	53.40	13.801	51.36	14.402	52.59	13.993

The results of one-way ANOVA showed that significant differences in age ($F(2, 7761) = 13.781$, $p < 0.001$) and years of fishing ($F(2, 7761) = 31.273$, $p < 0.001$) were found within the three identified recreational angler groups (Table 11). Furthermore, a one-way multivariate analysis of variance (MANOVA) was employed. The independent variable studied was *Cluster*, the three identified recreational angler groups. The dependent variables considered were age and years of fishing. Preliminary assumption testing was conducted to check for normality, linearity, univariate and multivariate outliers, homogeneity of variance-covariance matrices, and multicollinearity, with no serious violations noted.

The Box's Test of Equality of Covariance Matrices checks the assumption of homogeneity of covariance across the groups using $p < 0.001$ as a criterion. The results of the Box's Test of Equality of Covariance Matrices showed that there were no significant differences between the covariance matrices – as Box's M = 9.086, $F = 1.514$, $p = 0.169 > \alpha = 0.001$. Therefore, the assumption is not violated and Wilk's Lambda is an appropriate test to use.

A one-way MANOVA revealed a significant multivariate main effect for the three identified recreational angler groups, Wilks' Lambda = 0.992, $F(4, 15520) = 16.304$, $p < 0.001$, partial eta squared = 0.004. Power to detect the effect was 1.000. Given the significance of the overall test, the univariate main effects were examined. Significant univariate main effects for the three identified angler groups were obtained for age, $F(2, 7761) = 13.781$, $p < 0.001$, partial eta square = 0.004, power = 0.998; and years of fishing, $F(2, 7761) = 31.273$, $p < 0.001$, partial eta square = 0.008, power = 1.000.

According to the post-hoc comparisons with the Tukey HSD test, significant clustering pairwise differences were obtained both in age and years of fishing between the *Zonal and Catch Restrictions* cluster and both *Keep and Catch Restrictions* and *Seasonal Restrictions* clusters (Table 12).

Table 12: Post Hoc (Tukey HSD) Test among the Saltwater Recreational Angler Clusters

Dependent Variable	Group (I)	Group (J)	Mean Difference (I-J)	Std. Error	Sig.
Years of Fishing	Zonal and Catch Restrictions	Keep and Catch Restrictions	-1.42	0.474	0.008
	Zonal and Catch Restrictions	Seasonal Restrictions	2.45	0.536	0.000
	Keep and Catch Restrictions	Seasonal Restrictions	3.87	0.489	0.000
Age	Zonal and Catch Restrictions	Keep and Catch Restrictions	-0.96	0.378	0.030
	Zonal and Catch Restrictions	Seasonal Restrictions	1.07	0.427	0.032
	Keep and Catch Restrictions	Seasonal Restrictions	2.03	0.390	0.000

4.5 Multilayer Perceptron Neural Network Model

After the formation of the three identified recreational angler groups, a multilayer perceptron (MLP) neural network model was employed as a predictive model in deciding the recreational anglers' preferences toward recreational fishing management strategies. The Multilayer Perceptron Module of IBM SPSS Statistics 26 was used to build the neural network model and 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 predict recreational fishing management strategies, by analyzing data obtained from the saltwater recreational anglers. The data were randomly assigned to training (70%) and testing (30%) subsets. The training dataset is used to find the weights and build the model, while the testing data is used to find errors and prevent overtraining during the training mode (Table 13).

Table 13: Case Processing Summary

		N	Percent
Sample	Training	5410	69.7%
	Testing	2354	30.3%
Valid		7764	100.0%
Excluded		0	
Total		7764	

Neural network model is constructed with the multilayer perceptron algorithm. In order to find the best neural network, disparate possible networks were tested and it was concluded that neural network with a single input layer, a single hidden layer, and a single output layer was the best option for this study. Previous studies have found that using neural network with a single input layer, a single hidden layer, and a single output layer is advantageous. 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, a hyperbolic tangent activation function should be used for the single hidden layer of the model and linear activation function should be used for the output layer. The Multilayer Perceptron 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, automatic architecture selection chose 7 nodes for the hidden layer, while the output layer had 3 nodes to code the depended variable *Cluster*. For the hidden layer the activation function was the hyperbolic tangent, while for the output layer used the softmax function. Cross entropy was used as error function because of the use of softmax function (Table 14).

Table 14: Network Information

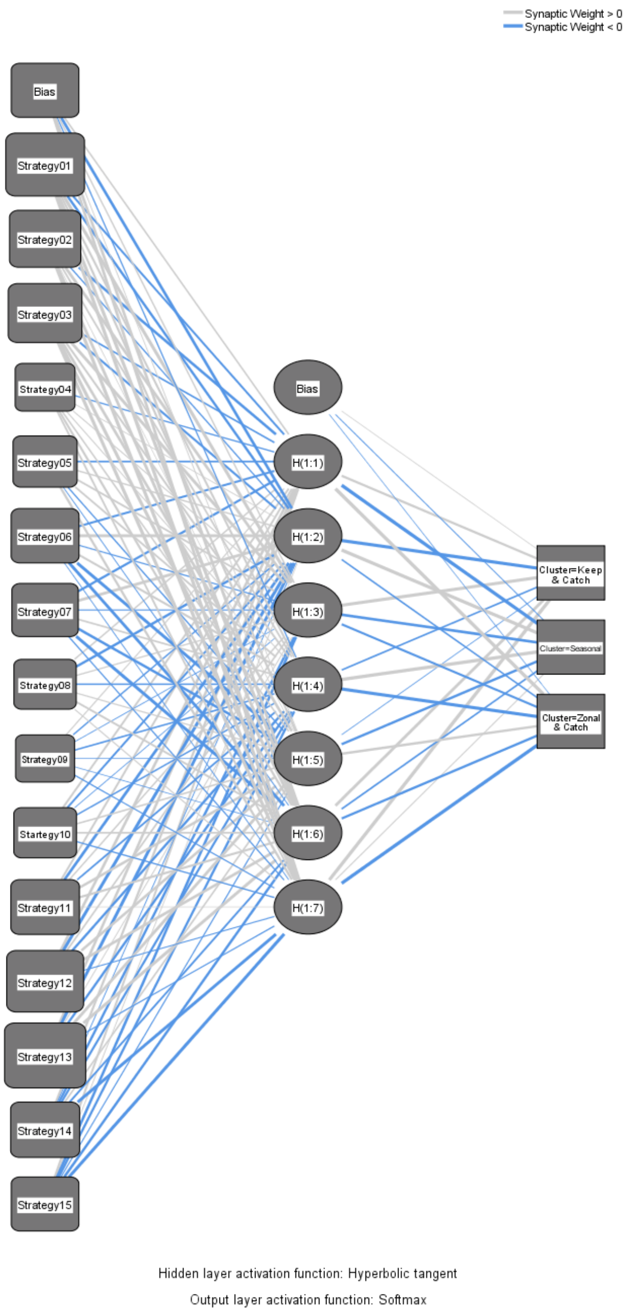
Input Layer	Covariates	1	Strategy01
		2	Strategy02
		3	Strategy03
		4	Strategy04
		5	Strategy05
		6	Strategy06
		7	Strategy07
		8	Strategy08
		9	Strategy09
		10	Strategy10
		11	Strategy11
		12	Strategy12
		13	Strategy13
		14	Strategy14
		15	Strategy15
	Number of Units[a]		15
	Rescaling Method for Covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		1

	Number of Units in Hidden Layer 1[a]		7
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	Cluster
	Number of Units		3
	Activation Function		Softmax
	Error Function		Cross-entropy

a. Excluding the bias unit

The network diagram showed the 15 input nodes, the 7 hidden nodes and the three output nodes representing the three identified recreational angler categories. In the architectural point of view, it was a 15-7-3 neural network, means that there were total 15 independent (input) variables, 7 neurons in the hidden layer and 3 dependent (output) variables (Figure 2).

Figure 2: Network Diagram



The model summary provided information related to the results of training and testing sample (Table 15). 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 (= 111.918) indicated the power of the model to predict the three identified recreational 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 and has learned to generalize from trend. The result justified the role of testing sample which was to prevent overtraining.

In this study the percentage of incorrect prediction was equal to 0.3% in the training sample. So the percentage of correct prediction was 99.7% which is an excellent prediction in a qualitative study for determining management results of recreational fisheries management strategies. The learning procedure was performed until 1 consecutive step with no decrease in error function was attained from the training sample.

Table 15: Model Summary

Training	Cross Entropy Error	111.918
	Percent Incorrect Predictions	0.3%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:01.67
Testing	Cross Entropy Error	53.188
	Percent Incorrect Predictions	0.5%

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

Using the training sample only, MLP neural network utilized synaptic weights to display the parameter estimates that showed the relationship between the units in a given layer to the units in the following layer (Table 16). Note that the number of synaptic weights can become rather large and that these weights are generally not used for interpreting neural network results (IBM, 2019).

Table 16: Parameter Estimates

Predictor		Predicted									
		Hidden Layer 1							Output Layer		
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	Keep & Catch	Seasonal	Zonal & Catch
Input Layer	(Bias)	0.443	-1.342	0.393	-0.298	0.099	1.275	1.322			
	S01	-0.799	-0.985	2.046	0.810	0.882	2.174	3.055			
	S02	-1.161	-0.348	1.365	0.638	0.008	1.423	2.556			
	S03	-0.534	-0.871	1.493	0.736	1.246	2.112	2.516			
	S04	-0.360	0.063	0.219	0.181	0.433	0.884	0.696			
	S05	-0.645	0.399	0.688	0.689	-0.394	-0.151	0.920			
	S06	-0.843	1.554	-0.278	0.863	-1.708	-1.491	-0.102			
	S07	-0.897	1.407	-0.210	0.603	-1.117	-1.727	-0.297			
	S08	0.420	-1.028	0.320	-0.438	0.272	0.704	0.264			
	S09	0.248	-0.397	-0.100	-0.524	-0.058	-0.043	-0.278			
	S10	0.708	-0.775	-0.060	-0.432	0.449	0.668	-0.372			
	S11	0.742	-1.351	0.414	-0.659	1.086	0.890	0.000			
	S12	1.201	-1.823	0.582	-0.951	1.126	1.315	-0.231			
	S13	1.138	-1.717	0.160	-0.930	1.414	1.616	-0.267			
	S14	0.896	-0.123	-0.979	-0.891	0.506	-0.698	-1.703			
	S15	0.821	0.100	-1.146	-0.924	-0.245	-1.053	-1.961			
Hidden Layer 1	(Bias)								0.030	-0.171	-0.009
	H(1:1)								0.923	-3.689	3.699
	H(1:2)								-2.156	2.632	-0.459
	H(1:3)								1.869	-1.271	-0.877
	H(1:4)								-0.624	2.995	-2.071
	H(1:5)								-0.079	-0.995	1.001
	H(1:6)								1.488	-0.632	-0.971
	H(1:7)								3.510	0.189	-3.419

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 recreational angler groups, by partition and overall (Table 17). As can be seen, the MLP neural network correctly classified 5395 recreational anglers out of 5409 in the training sample and 2342 out of 2353 in the testing sample. Overall 99.7% 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 2416 *Keep and Catch Restrictions* recreational anglers into the *Keep and Catch Restrictions* group, out of 2422. It held 99.8% classification accuracy for the *Keep and Catch restrictions* group. Similarly, the same model was able to classify 1417 *Seasonal restrictions* recreational anglers into the *Seasonal Restrictions* group out of 1421, and 1562 *Zonal and Catch Restrictions* recreational anglers into the *Zonal and Catch Restrictions* group out of 1569. It was able to generate 99.7% classification accuracy for both the *Seasonal Restrictions* and *Zonal and Catch Restrictions* groups (Table 17).

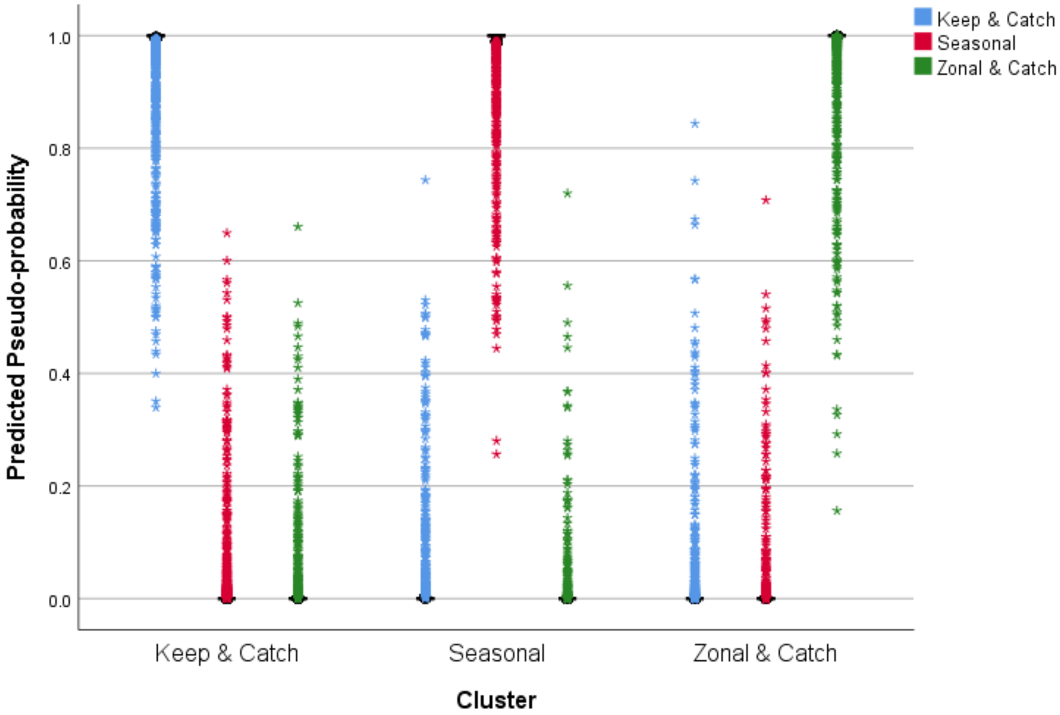
Table 17: Predictive Ability and Classification Results

Classification					
Sample	Observed	Predicted			
		Keep & Catch	Seasonal	Zonal & Catch	Percent Correct
Training	Keep & Catch	2416	5	1	99.8%
	Seasonal	3	1417	1	99.7%
	Zonal & Catch	3	2	1562	99.7%
	Overall Percent	44.8%	26.3%	28.9%	99.7%
Testing	Keep & Catch	1054	2	1	99.7%
	Seasonal	3	608	1	99.3%
	Zonal & Catch	4	1	680	99.3%
	Overall Percent	45.1%	26.0%	29.0%	99.5%

Dependent Variable: Cluster

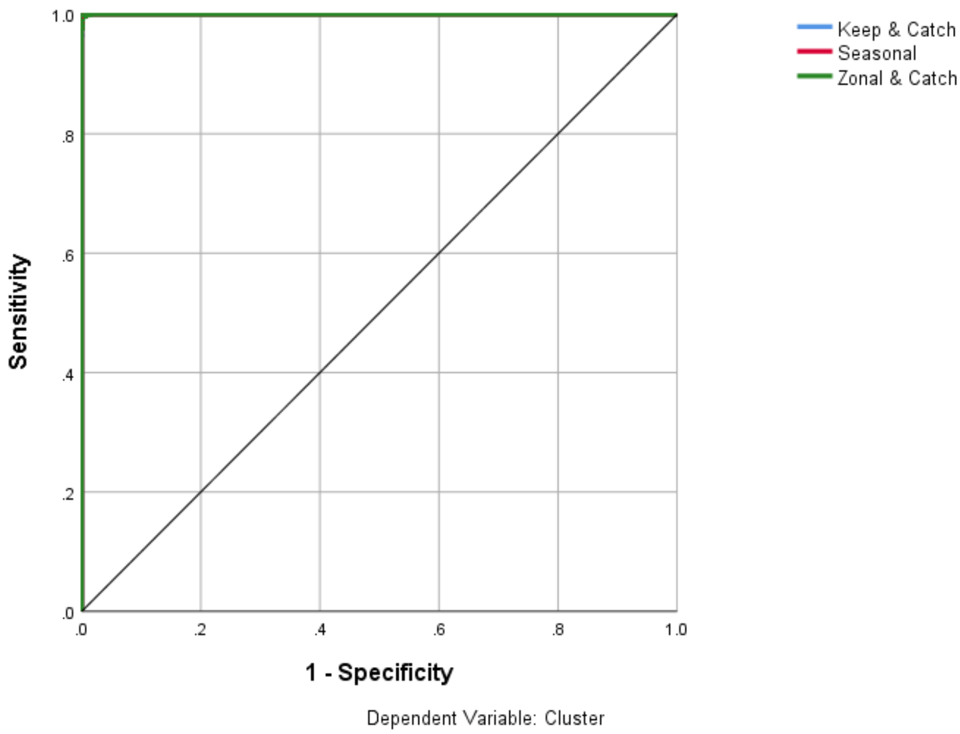
For the dependent variable *Cluster*, the following chart displayed boxplots that classified the predicted pseudo-probabilities based on the whole dataset (IBM, 2019). For each boxplot, the values above 0.5 show correct predictions. The first, from the left, boxplot showed the predicted probability of the observed *Keep and Catch Restrictions* recreational anglers to be in the *Keep and Catch Restrictions* category. The second and third boxplots showed that the probability for a recreational angler to be classified in *Keep and Catch Restrictions* category although he/she really was in *Seasonal Restrictions* and *Zonal and Catch Restrictions* categories, respectively. The fourth boxplot showed, for outcomes that have observed category *Seasonal Restrictions*, the predicted probability of category *Keep and Catch Restrictions*. The right boxplot showed, the probability a recreational angler who really *Zonal and Catch Restrictions* category to be classified in the *Zonal and Catch Restrictions* category (Figure 3).

Figure 3: Predicted-by-Observed Chart



The ROC curve is a diagram of sensitivity versus specificity that shows the classification performance for all possible cutoffs (IBM, 2019). It gives the sensitivity and specificity (= 1 – false positive rate) chart, based on the combined training and testing samples. The 45-degree line from the upper right corner of the chart to the lower left represents the scenario of randomly guessing the class. The more the curve moves away the 45-degree baseline, the more accurate is the classification (Figure 4).

Figure 4: ROC Curve



The area under the ROC curve (IBM, 2019) showed that, if a recreational angler from the *Keep and Catch Restrictions* category and a recreational angler from the *Seasonal Restrictions* category were randomly selected, there was 100% (1.000) probability that the model-predicted pseudo-probability for the first recreational angler of being in the *Keep and Catch Restrictions* category, was higher than the model-predicted pseudo-probability for the second recreational angler of being in the *Keep and Catch Restrictions* category (Table 18).

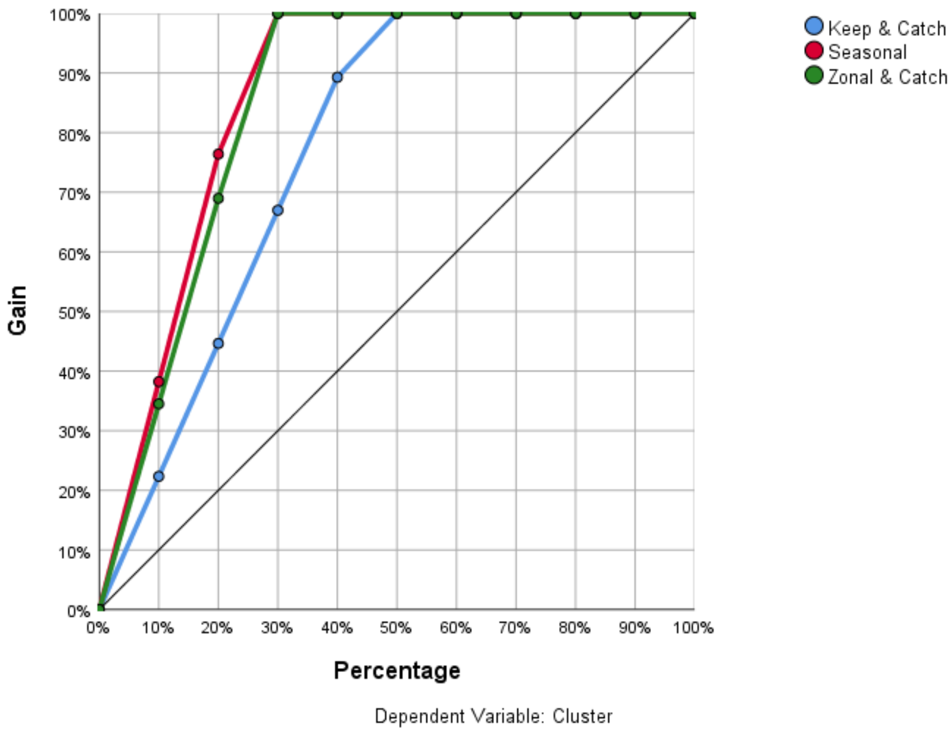
Table 18: Area under the Curve

		Area
Cluster	Keep & Catch	1.000
	Seasonal	1.000
	Zonal & Catch	1.000

The Cumulative Gains chart is the presentence of correct classifications obtained by the MLP neural network model against the correct classifications that could result by chance (i.e. without using the model) (IBM, 2019). Gain is a measure of the effectiveness of a classification model calculated as the percentage of correct predictions obtained with the model, versus the percentage of correct predictions obtained without a model (baseline). The farther above the baseline a curve lies, the greater the gain. A higher overall gain indicates better performance.

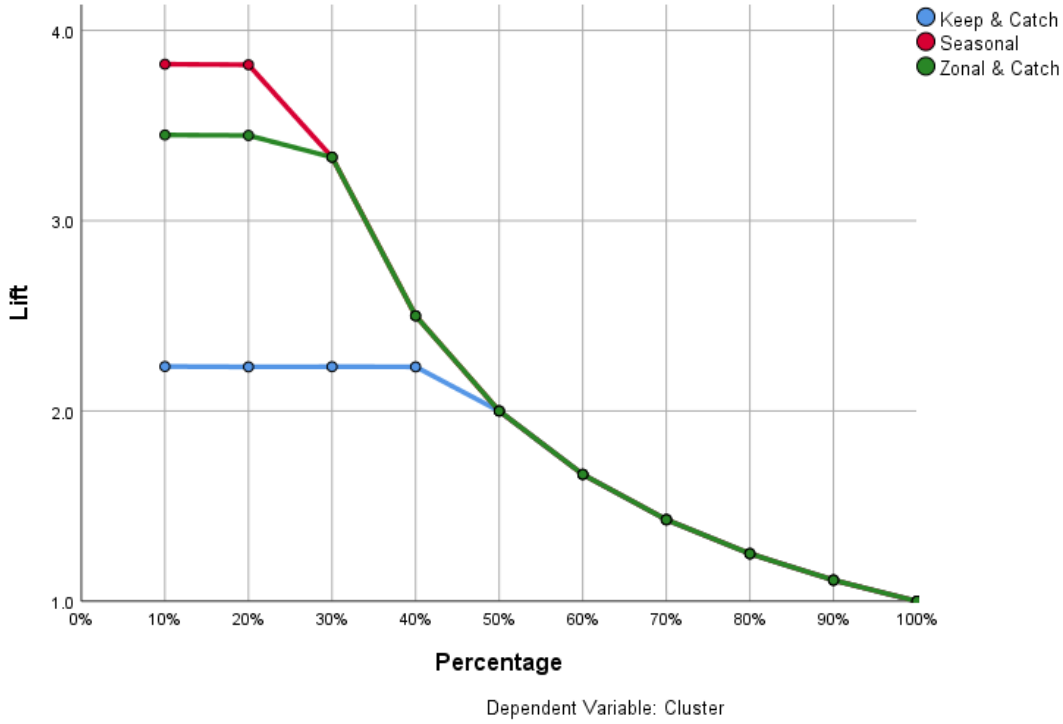
For example, the second point on the curve for the *Zonal and Catch Restrictions* category was at (20%, 70%), meaning that if the network score a dataset and sort all of the cases by predicted pseudo-probability of *Zonal and Catch Restrictions*, it would be expected the top 20% to contain approximately 70% of all of the cases that actually take the category *Zonal and Catch Restrictions*. The selection of 100% of the scored dataset, obtained all of the observed *Zonal and Catch Restrictions* cases in the dataset (Figure 5).

Figure 5: Cumulative Gains Chart



Lift chart, as well as cumulative gains chart, is visual aids for evaluating performance of classification models (IBM, 2019). However, in contrast to the confusion matrix that evaluates models on the whole population, gains or lift chart evaluates model performance in a portion of the population. A lift chart uses a part of the dataset to give a clear view of the benefit to use a model in contrast to not using a model. The values from the gains diagram were used to calculate the lift factor (i.e. the benefit): the lift at 70% for the category *Zonal and Catch Restrictions* was 70%/20% = 3.5 (Figure 6).

Figure 6: Lift Chart



The importance of the individual independent variables (factor influencing recreational fisheries management strategies) is a measure of how much the neural network model predicted value changes for different independent variables. The input parameters -- recreational fisheries management strategies which influenced the three identified recreational angler groups have been ranked by the neural network model were given in the following Table 19.

The first three significant dominant factors that have been found were "protect and restore fish habitat that has been degraded" (100%), contributed the most in the neural network model construction, followed by "establish minimum size limits of the fish you can keep" (90.6%), and "provide artificial fish habitat (e.g. artificial reef) in some areas of the ocean" (84.1%), had the greatest effect on how the recreational anglers' preferences, in terms of recreational fisheries management strategies. The next two important factors were "limit the total number of fish you can keep" (72.7%) and "establish maximum size limits of the fish you can keep" (63.5%).

The other factors were relatively not important such as "restrict certain types of fishing gear" (31.7%), "increase the recreational harvest limit by decreasing the commercial harvest limit" (30.3%), "manage some species as catch-and-release only" (20.7%), and the least important factor which has been identified was "divide the recreational harvest limit among different modes (e.g. private anglers and for-hire/charter boat anglers)" (18.1%).

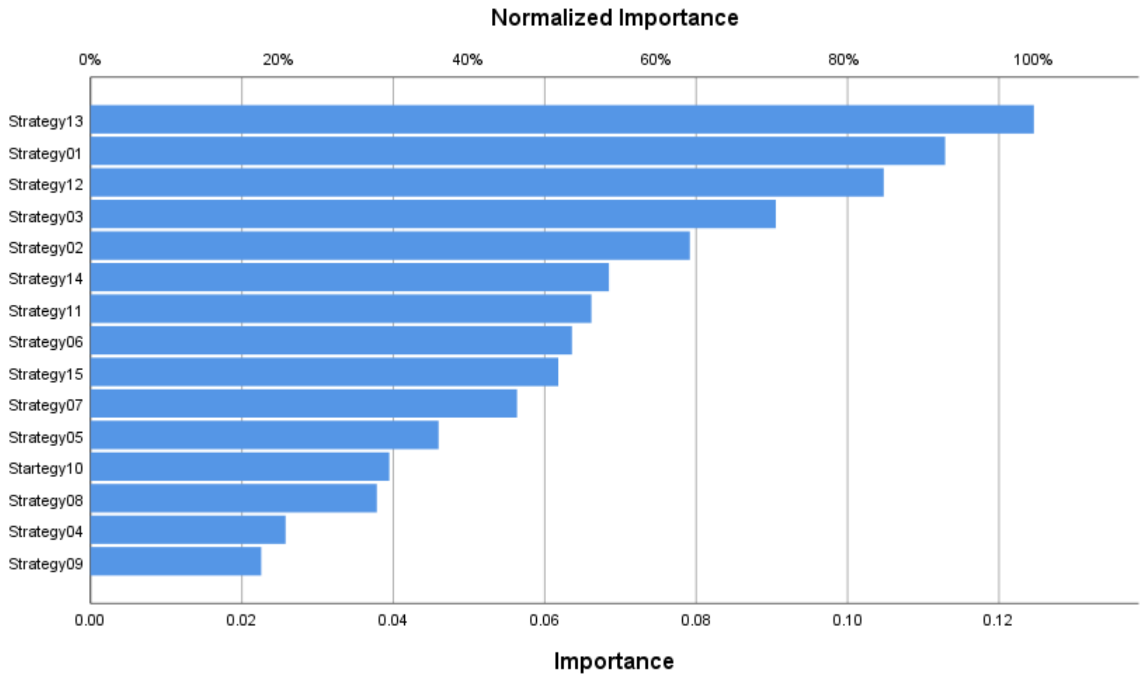
Table 19: Independent Variable Importance Analysis

Please state your preference for using each strategy listed below	Importance	Normalized Importance	Rank
Establish minimum size limits of the fish you can keep	0.113	90.6%	2
Establish maximum size limits of the fish you can keep	0.079	63.5%	5
Limit the total number of fish you can keep	0.091	72.7%	4
Manage some species as catch-and-release only	0.026	20.7%	14

Establish longer seasons with more restrictive bag limits	0.046	36.9%	11
Establish shorter seasons with less restrictive bag limits	0.064	51.0%	8
Establish shorter seasons with a larger variety of species you can legally catch	0.056	45.2%	10
Increase the recreational harvest limit by decreasing the commercial harvest limit	0.038	30.3%	13
Divide the recreational harvest limit among different modes (e.g. private anglers and for-hire/charter boat anglers)	0.023	18.1%	15
Restrict certain types of fishing gear	0.039	31.7%	12
Require the use of release techniques that reduce fish mortality	0.066	53.1%	7
Provide artificial fish habitat (e.g. artificial reef) in some areas of the ocean	0.105	84.1%	3
Protect and restore fish habitat that has been degraded	0.125	100.0%	1
Designate some areas of the ocean as marine reserves with catch-and-release fishing only	0.068	55.0%	6
Close some areas of the ocean for certain seasons	0.062	49.6%	9

Independent variable importance chart showed the impact of each independent variable in the MLP neural network model in terms of relative and normalized importance (IBM, 2019). Independent variable importance chart also depicted the importance of the independent variables, i.e. how sensitive is the model is the change of each input variable (Figure 7).

Figure 7: Independent Variable Importance Chart



5. Discussion and Conclusion

Understanding saltwater recreational anglers' preferences of recreational fisheries management strategies could be one of many critical factors to the effectiveness of responsive and adaptive marine resource management programs. This study attempted to provide insight into saltwater recreational anglers' preferences toward recreational fisheries management strategies. Thus, the main purpose of this paper was to explore segmentation of the recreational angler population based on certain preferences of interest regarding recreational fisheries management strategies using psychometric data, while also estimating the size of recreational angler subgroups that have been identified, which may be useful for saltwater recreational fisheries managers to prioritize and effectively allocate fisheries management initiatives and resources.

Through cluster analysis, three groups were identified based on similar recreational fisheries management strategy preferences. The largest of these three groups, *Keep and Catch Restrictions* cluster, was associated to preferences for restricting and developing recreational fishing, but not for the prohibition of recreational fishing based on geographic area, nor time of year. This preference is reflected within a number of studies, which have examined the motivations of recreational anglers. Non-catch motivations have been found to be more motivating than catch motivations. Recreational anglers are motivated by the benefits derived from the relaxation recreational angler's experience.

Both of the two largest clusters, the *Zonal and Catch Restrictions* and *Keep and Catch Restrictions* clusters, demonstrated positive, strong associations to the more sustainability-themed recreational fisheries management strategies. The creation of new fisheries habitat and the restoration of degraded fisheries habitat are two examples of such sustainability-themed recreational fisheries management strategies.

Furthermore, the benefits derived from the interaction with the natural environment provides significant motivation for recreational anglers (Driver and Knopf, 1976). In addition, recreational anglers are motivated by the benefits derived from the social interaction with friends and family experienced while recreationally fishing (Schroeder et al., 2008). As a result, recreational angler's acceptance of recreational fisheries management strategies, which include catch restrictions and long-term sustainable development, is likely. However, recreational fisheries management strategies, which prohibit fishing entirely, will be less acceptable. The most important incentive motivating anglers, related to recreational fisheries management, is dedicated access to fisheries (Hilborn, 2007).

Further analysis, utilizing the Chi-square test, did yield some significant difference among respondents based on their gender. Although females made up only 16% of the total respondents, they did demonstrate more preference for geographic/zone restrictions and less preference for catch restrictions compared to male respondents. Regarding regional differences, a higher proportion of the respondents preferring seasonal restrictions, for example, were located in the Alaska, West Coast, and North Atlantic regions.

Furthermore, a higher proportion of the respondents preferring geographic/zone restrictions were located in the Mid-Atlantic, South Atlantic, and Gulf of Mexico regions. Further differences and similar results related to both gender and region were identified through multinomial logistic regression analysis. Fewer differences among groups were identified related to socio-demographic variables including, respondent income, education, and age.

The 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 multi-layered 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 analysis was employed as a predictive model in deciding recreational anglers' preferences toward recreational fishing management strategies. From an architectural perspective, it showed a 15-7-3 neural network. The results also revealed that fisheries habitat development and bag limit consideration were the greatest effect on how the recreational anglers' preferences in terms of recreational fisheries management strategies.

Developing insight into the preferences of saltwater anglers related to recreational fisheries management strategies may be critical to their successful implementation and acceptance. Continued monitoring of saltwater angler fisheries management strategy preferences will provide a more longitudinal perspective based on repeated observations over time to allow for further analysis and for the identification of change or differences related to each variable of concern. There is a lack of longitudinal perspective related to anglers' preferences and behavior (Tseng et al., 2012).

This study attempted to identify groups exhibiting common patterns of responses, and to examine the association between socio-demographic characteristics and which recreational fisheries management strategy they preferred. Results of this study may provide insight regarding the preferences toward recreational fisheries management strategies from saltwater recreational anglers as an indicator of potential participation and behavior of saltwater recreational fisheries management.

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