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Cluster Analysis of Personality Types Using Respondents' Big Five Personality Traits

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ABSTRACT

This study utilized a mixed model approach, incorporating k-means clustering analysis for data examination, discriminant analysis for classification, and multilayer perceptron neural network analysis for prediction. After removing inadequate samples and outliers, the total number of observations was 19,692 for this study, which was collected through an interactive online personality test (i.e., Big Five Personality Traits) in 2012. The empirical results based on the k-means clustering analysis identified four different personality clusters using the total score of Big Five Personality Traits (Extraversion, Neuroticism, Agreeableness, Conscientiousness, and Openness to Experience). The empirical results obtained from the k -means clustering analysis revealed the presence of four distinct personal clusters, determined by the total scores of the Big Five Personality Traits. The accuracy of the clustering analysis was further tested using discriminant analysis, which indicated significant difference among the cluster means and correctly classified 95.5% of the original grouped cases. For predictive modeling, a multilayer perceptron neural network framework was used. The network had a 5-6-4 structure and was employed to determine the personality classification of participants. Notably, the model achieved 99.4% accuracy in correctly classifying the training grouped cases and 99.2% accuracy for the testing grouped cases. The results of this study offer valuable insights into understanding the personalities of participants, with implications for various domains such as psychology, social sciences, cultural studies, and economics.

1. Introduction

The American Psychological Association (APA), as defined in the Encyclopedia of Psychology, describes personality as "individual differences in characteristic patterns of thinking, feeling, and behaving" (https://www.apa.org/topics/personality). In the APA Dictionary of Psychology, a personality trait is defined as "a relatively stable, consistent, and enduring internal characteristic inferred from an individual's pattern of behaviors, attitudes, feelings, and habits in the individual" (https://dictionary.apa.org/personality-trait). Therefore, personality traits represent the characteristic patterns of thoughts, feelings, and behaviors that exhibit consistency and stability. For instance, an individual with a high score on a specific trait, such as Extraversion, is expected to display sociability across different situations and over time.

Studying personality traits is valuable for summarizing, predicting, and explaining an individual's behavior, with significant implications. The most common approach for assessing traits is through personality tests, where individuals self-report their own characteristics. The widely adopted system of traits is known as the Big Five Personality Test, encompassing five broad traits represented by the acronym OCEAN: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism.

The Big Five Personality Test assesses five core personality traits, providing a comprehensive understanding of each trait and offering insights into the individual's fundamental personality characteristics. This test illuminates "the breadth, depth, originality, and complexity of an individual's mental and experiential life" (John and Srivastava, 1999). Moreover, each of the major traits within the Big Five can be further divided into facets, enabling a more detailed and nuance analysis of an individual's personality.

The Big Five personality traits can be described as (1) Extraversion: this trait measures the extent to which individuals engage with the external world and experience enthusiasm and positive emotions. (2) Agreeableness: this trait reflects the extent to which individuals value cooperation, social harmony, honesty, decency, and trust worthiness. Agreeable individuals also tend to have an optimistic view of human nature. (3) Conscientiousness: this trait assesses extent to which individuals value planning, exhibit persistence, and are oriented towards achieving their goals. (4) Neuroticism: this trait measures the extent to which individuals experience negative feelings and have a tendency to emotionally overreact. (5) Openness to Experience: this trait gauges the extent to which individuals demonstrate intellectual curiosity, self-awareness, and a willingness to embrace individualism or nonconformity (Rossberger, 2014).

In recent years, numerous studies have focused on understanding human personality classification through advanced techniques. Notable studies include Tighe et al. (2016), Gerlach et al. (2018), Souri et al. (2018), Ahmad et al. (2020), Khan et al. (2020), Talasbek et al. (2020), Gaisendrees et al. (2020). In particular, Gerlach et al. (2018) proposed four personality types – Role Model, Average, Reserved, and Self-Centered – based on extensive analysis over a million participants across four large data sets. This research has sparked further discussions within the academic community, as evidenced by subsequent studies by Freudenstein et al. (2019), Gerlach et al. (2019), Katahira et al. (2020).

This study aimed to explore the classification of participants based on specific aspects of interest related to the Big Five Personality Traits. Additionally, it sought to investigate how participants' behavior could be identified by using a multilayer perceptron neural network framework, utilizing information obtained from traditional surveys. Moreover, by capturing current trends in participants' perceptions, the multilayer perceptron neural network could predict future outcomes within a campaign.

Therefore, the main objectives of this study were as follows: (1) to understand participants' perceptions of the Big Five Personality Traits, (2) to identify participant groups exhibiting common patterns of responses regarding the Big Five Personality Traits, and (3) to classify participants based on the Big Five Personality Traits using the multilayer perceptron neural network approach. This paper is organized as follows: The second section describing the Big Five Personality Traits data source. The third section includes the methodology, and the fourth section demonstrates the empirical results using k -means cluster analysis, discriminant analysis, profile analysis, and the multilayer perceptron neural network. The final sections provide concluding remarks and discuss further implications.

2. Materials and Methods

The data used in this study was extracted from responses to the Big Five Personality Test, which was constructed using items from the International Personality Item Pool (https://openpsychometrics.org/_rawdata/). This data was collected through on interactive online personality test in 2012. Participants were informed about the research purpose and the recording of their responses at the beginning of the test. They were also asked to confirm their consent at the end of the test. The respondents were presented with 50 statements, with ten questions addressing each personality factor (Table 1). The five-point Likert scale was used, where 1 = Disagree, 3 = Neutral, 5 = Agree, and 0 = missed.

Table 1. The Big Five Personality Traits

Extraversion = SUM(E1:E10)	
E1	I am the life of the party.
E2	I don't talk a lot.
E3	I feel comfortable around people.
E4	I keep in the background.
E5	I start conversations.
E6	I have little to say.
E7	I talk to a lot of different people at parties.
E8	I don't like to draw attention to myself.
E9	I don't mind being the center of attention.
E10	I am quiet around strangers.
Neuroticism = SUM(N1:N10)	
N1	I get stressed out easily.
N2	I am relaxed most of the time.
N3	I worry about things.
N4	I seldom feel blue.
N5	I am easily disturbed.
N6	I get upset easily.
N7	I change my mood a lot.
N8	I have frequent mood swings.
N9	I get irritated easily.
N10	I often feel blue.
Agreeableness = SUM(A1:A10)	
A1	I feel little concern for others.
A2	I am interested in people.
A3	I insult people.
A4	I sympathize with others' feelings.
A5	I am not interested in other people's problems.
A6	I have a soft heart.
A7	I am not really interested in others.
A8	I take time out for others.
A9	I feel others' emotions.
A10	I make people feel at ease.
Conscientiousness = SUM(C1:C10)	
C1	I am always prepared.
C2	I leave my belongings around.
C3	I pay attention to details.
C4	I make a mess of things.
C5	I get chores done right away.
C6	I often forget to put things back in their proper place.
C7	I like order.
C8	I shirk my duties.
C9	I follow a schedule.
C10	I am exacting in my work.
Openness to Experience = SUM(O1:O10)	
O1	I have a rich vocabulary.
O2	I have difficulty understanding abstract ideas.
O3	I have a vivid imagination.
O4	I am not interested in abstract ideas.
O5	I have excellent ideas.
O6	I do not have a good imagination.
O7	I am quick to understand things.
O8	I use difficult words.

O9	I spend time reflecting on things.
O10	I am full of ideas.

The initial sample size of the first dataset was 19,719. After removing 11 inadequate samples and 16 outliers, the total number of observations available for further analysis to examine the psychometric properties of the Big Five Personality Traits was 19,692. The sum of each personality trait within the Big Five was used for this study (Table 2).

Table 2. Descriptive Statistics of the Big Five Personality Traits

	Mean	Median	Standard Deviation
Extraversion (EE)	30.78	31.00	3.48
Neuroticism (NN)	30.97	31.00	6.70
Agreeableness (AA)	32.06	32.00	3.50
Conscientiousness (CC)	31.56	32.00	3.85
Openness to Experience (OO)	33.15	33.00	3.80

Source: Own Calculation

The participants also provided the information as follows:

Table 3. Information of the participants

Variable	Description
age	individuals reporting age < 13 were not recorded
gender	1 = Male, 2 = Female, 3 = Other (0 = missed)
race	1 = Mixed Race, 2 = Arctic (Siberian, Eskimo), 3 = Caucasian (European), 4 = Caucasian (Indian), 5 = Caucasian (Middle East), 6 = Caucasian (North African, Other), 7 = Indigenous Australian, 8 = Native American, 9 = North East Asian (Mongol, Tibetan, Korean Japanese, etc.), 10 = Pacific (Polynesian, Micronesian, etc.), 11 = South East Asian (Chinese, Thai, Malay, Filipino, etc.), 12 = West African, Bushmen, Ethiopian, 13 = Other (0 = missed)
engnat	Response to "is English your native language?" 1 = yes, 2 = no (0 = missed)
hand	"What hand do you use to write with?" 1 = Right, 2 = Left, 3 = Both (0 = missed)
source	How the participant came to the test. Based on HTTP Referer. 1 = from another page on the test website, 2 = from google, 3 = from facebook, 4 = from any url with ".edu" in its domain name (e.g. xxx.edu, xxx.edu.au), 5 = other source, or HTTP Referer not provided.

3. Methods

This study incorporated a mixed model approach, utilizing k-means clustering analysis to examine the data, discriminant analysis for classification, and multilayer perceptron neural network for prediction purposes. Clustering is a commonly used technique in market segmentation to identify similarities among customers or discover entirely new segments. Specifically, k-means clustering analysis is used to identify unlabeled clusters within the data, confirming existing business assumptions or revealing unknown groups within complex datasets.

Empirically, the k-means clustering analysis aims to identify homogeneous clusters within the data, with data points in each cluster exhibiting similarity within the cluster and differences between clusters. This is achieved by using a similarity measure, such as a Euclidean-based distance (Bishop, 2006). Methodologically, k-means is an iterative algorithm that groups observations around geometric centers known as centroids to form clusters (Child, 2006). The algorithm calculates the centroids, which are determined by the analyst, and assigns data points to the cluster with the least distance between its centroid and the data point. Once the algorithm is executed and the groups are defined, new data can be easily assigned to the appropriate group.

Discriminant analysis is often used in conjunction with k-means clustering analysis. It is a statistical technique used to classify the target population into specific categories or clusters based on certain attributes known as independent variables (Beatley, 1991). Prior knowledge of some cluster assignments is required for any discriminant analysis. It serves as a method for predicting the level of a one-way classification using known values of the responses.

For any kind of discriminant analysis, some cluster assignments should be known beforehand. Discriminant analysis is also a method of predicting some level of a one-way classification based on known values of the responses. The effectiveness of the set of variables in predicting category membership is determined based on their proximity to the multivariate means of the predicted levels. Put simply, discriminant analysis helps determine the predictive power of a set of variables in identifying category membership (Cronbach, 1951).

Various multivariate analytical techniques can be utilized to create post hoc market segments. Among them, neural networks have gained significant popularity, particularly in the field of marketing. Neural networks play a crucial role in market segmentation by enabling the classification or grouping of customers based on their characteristics. Essentially, neural networks emulate the problem-solving approach of the human brain, making them a powerful computing technique. They are widely recognized as one of the most popular methods in machine learning, capable of performing tasks such as classification, clustering, and prediction.

According to Haykin (2009), neural networks are constructed by connecting artificial neurons, which serve as the fundamental components for processing information within the network. Mathematically, the output of a neuron can be represented as:

$$f(x) = \varphi(\textstyle\sum_{i=1} x_i w_i + b) \qquad i = 1, \dots, n \tag{1}$$

Here, x_i refers to the input features, w_i represents the weights assigned to each input, b denotes the bias that is combined with the weighted inputs to generate the net inputs, and φ represents the non-linear activation function. The bias and weights are adjustable parameters of the neuron and thus, a mapping mechanism is necessary to connect the input and output of the neuron. This mapping mechanism is commonly referred to as the activation function (Haykin, 2009).

A simple perceptron is a linear classifier that takes multiple real-valued inputs and produces a single output by computing a linear combination using its input weights. On the other hand, a multilayer perceptron (MLP) (Figure 1) is composed of multiple layers of working units that are typically interconnected in a feed-forward manner. Each neuron in one layer is connected to the neurons in the subsequent layer through directed connections. In terms of its theoretical capabilities, the MLP is considered a universal approximator, meaning it has the ability to construct any nonlinear mapping with a high degree of accuracy (Hornik et. al., 1989). Unlike other methods, the MLP does not require any prior assumptions or predefined models about the data properties (Bishop, 2006).

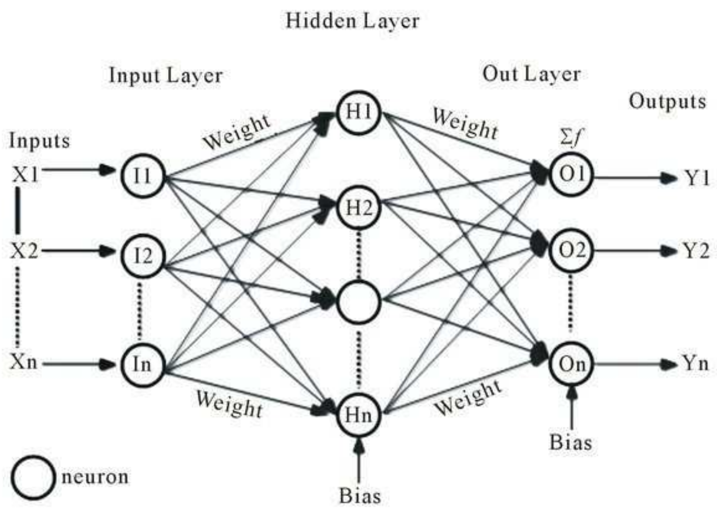

Figure 1. Single Hidden Layer MLP (Adapted from El-Amir and Hamdy, 2020)

According to Gardner and Dorling (1998), a multilayer perceptron is described as a system of interconnected nodes or neurons, serving as a model for nonlinear mapping between an input vector and an output vector. The multilayer perceptron (MLP) is widely used in neural network applications, particularly with the back-propagation training algorithm for multilayer feed-forward networks. MLP is comprised of perceptrons organized into layers, including an input layer, one or more hidden layers, and an output layer.

Each perceptron calculates the sum of its weighted inputs and applies an activation function to the result. This output is then forwarded to the next layer in the network. The output layer consists of perceptrons equal to the number of classes, and the perceptron with the highest activation is considered as the classification for the input sample. Training is accomplished by iteratively presenting all training samples to the networks and comparing the output with the corresponding true class label (Haykin, 2009).

The multilayer perceptron (MLP) is renowned as one of the most popular neural network methods due to its extensive utilization across various practical applications. One key advantage is its ability to learn non-linear representations, making it highly versatile for tasks such as modeling, prediction, classification, clustering, and optimization (Ahmed, 2005; De Gooijer and Hyndman, 2006; Bose, 2007; Zacharis, 2016; Ramchoun et al., 2017; Do et al., 2019).

Additionally, a multinomial logistic regression analysis (MLR) is utilized to examine the relationship between selected variables and personality type memberships. The MLR is particularly useful for analyzing the effects of independent variables on a finite number of choices, providing an appropriate framework to explain choices based on individual-specific data (Greene, 2008). It extends of the binary logit model by accommodating more than two values for the dependent variable.

In the MLR, the dependent variable can be explained based on the individual-specific explanatory variables for each personality type, resulting in a vector of estimated parameters for each personality type. One way to interpret the relationship between a predictor and the dependent variable is by calculating predicted probabilities. The predicted probability for the ith individual that belong to the personality type j can be computed as:

$$Prob(Y_i = j) = \frac{\exp(\beta_j{'}x_i)}{\sum_i \exp(\beta_j{'}x_i)} \quad for\, j = 1,2,3,4 \tag{2}$$

Here, Y_i represents the dependent variable associated with the personality type j, x_i is the vector of independent variables associated to individual i, and β_j is the coefficient vector of parameters associated to the personality type j. The estimation is performed by maximizing the likelihood function (Greene, 2008).

4. Results

4.1 K-Mean Clustering Analysis

The application of k-means clustering analysis techniques aims to assign objects to groups in a manner that maximized similarity within groups and difference between groups (Churchill and Iacobucci, 2005). In this study, a k-means clustering analysis was applied to identify homogeneous clusters within the 19,692 respondents based on the sum of each personality trait of the Big Five personality traits. As a result, a four-cluster solution was identified, which was labeled as Role Models, Average, Reserved, and Self-Centered clusters, representing distinct personality types (Gerlach et al., 2018).

The Role Models personality type, which accounted for 27.2 percent of the respondents, exhibited above-average scores in Extraversion, Agreeableness, Conscientiousness, and Openness to Experience, except for significantly below-average scores in Neuroticisms compared to the overall sample. The Average personality type, comprising the largest group at 32.8 percent of respondents, displayed below-average scores in Extraversion, Agreeableness, Conscientiousness, and Openness to Experience, but had significantly higher scores in Neuroticism compared to the overall sample.

The Reserved personality type, the smallest group consisting of 17.4 percent of the respondents, received above-average scores in all five personality traits. On the other hand, the Self-Centered personality type, representing 22.6 percent of the respondents, had below-average scores in all five personality traits (Table 4).

Table 4. K-Means Clustering Analysis of Respondents' Big Five Personality Traits

	Role Models		*Average*		*Reserved*		*Self-Centered*	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Extraversion	31.52	3.20	29.63	3.12	32.76	3.87	30.03	3.08
Neuroticism	24.39	3.86	35.41	3.34	38.27	4.06	26.80	3.53
Agreeableness	32.41	3.15	31.43	3.09	34.86	3.36	30.40	3.19
Conscientiousness	32.51	3.09	30.89	3.22	35.09	3.58	28.67	3.07
Openness to Experience	34.80	2.86	32.50	3.45	35.60	3.50	30.23	3.19
n = 19692	5348		6463		3424		4457	
Percentage	27.2%		32.8%		17.4%		22.6%	

Source: Own Calculation

4.2 Discriminant Analysis

Discriminant analysis is a statistical technique to classify the target population into specific categories or groups based on the certain attributes, also known as predictor variables or independent variables (Fisher, 1936; Tabatchnick and Fidell, 2013). The main objective of discriminant analysis is to develop discriminant functions, which are linear combination of independent variables that effectively discriminate between categories of the dependent variable. This analysis helps determine if there are significant differences among groups, in terms of the independent variables and assess the accuracy of the classification (Cronbach, 1951).

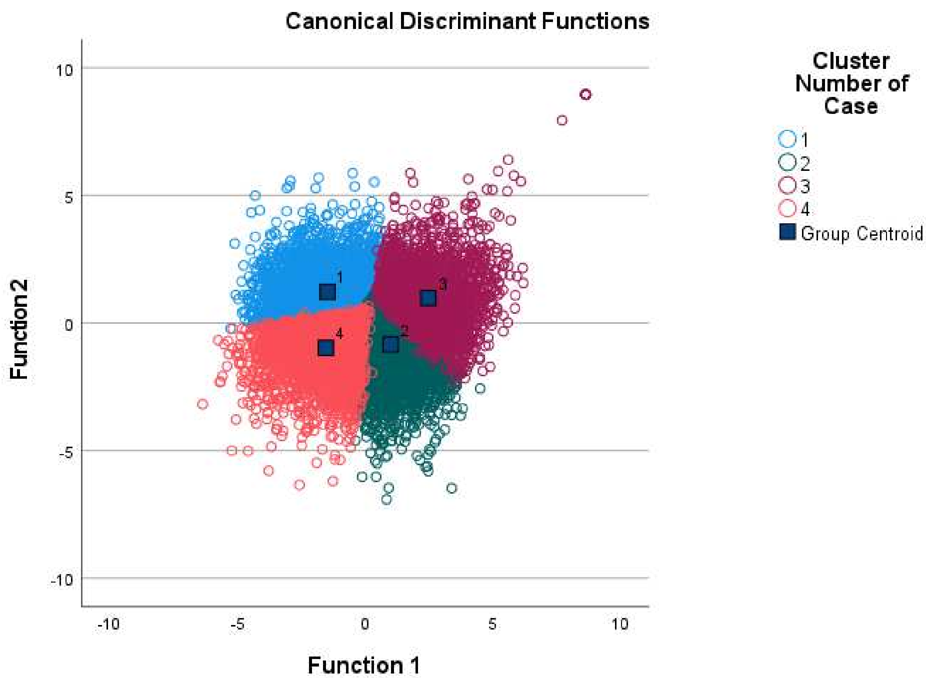

Figure 2. Territorial Map (1 = Role Models; 2 = Average; 3 = Reserved; 4 = Self-Centered)
Source: Own Calculation

To validate the accuracy of the k-means clustering results, a complementary linear discriminant analysis employed. Linear discriminant analysis is primarily used to predict membership in two or more mutually exclusive groups. In this study, it was used to classify the 19,692 respondents into specific personality types based on their answers related to the Big Five Personality Traits.

The Wilk's Lambda scores for the discriminant functions were 0.137 ($\chi 2$ = 39187.935, df = 15, p < 0.001), 0.481 ($\chi 2$ = 14414.262, df = 8, p < 0.001), and 0.970 ($\chi 2$ = 608.067, df = 3, p < 0.001), respectively, indicating significant differences in group means. Additionally, a territorial map, presented in Figure 2, was used as a visual tool to assess the results of the discriminant analysis by plotting the group membership of each case on a graph.

Based on the results of the discriminant analysis, it was found that 5,348 cases fell into the Role Models personality type, 6,463 cases fell into the Average personality type, 3,424 cases fell into the Reserved personality type, and 4,457 cases fell into the Self-Centered personality type, based on the original row totals, which represent the frequencies of groups found in the data (Table 5).

By examining each row, the number of cases in each group can be classified according to this analysis. For instance, out of the 5,348 cases classified as the Role Models personality type, 5,135 were accurately predicted, while 213 were incorrectly predicted (3 were predicted to be in the Average personality type, 37 were predicted to be in the Reserved personality type, and 173 were predicted to be in the Self-Centered personality type).

The predicted group membership provides the expected frequencies of groups resulting from the analysis. The numbers listed down each column indicate the correct and incorrect classifications. For example, out of the 5,376 cases predicted to be in the Role Models personality type, 5,135 were accurately predicted, and 241 were incorrectly predicted (101 cases were actually in the Average personality type, and 140 cases were actually in the Self-Centered personality type).

Table 5. Classification Results Based on the Discriminant Analysis

		Personality Type	Predicted Group Membership				
			Role Models	*Average*	*Reserved*	*Self-Centered*	Total
Original	Count	*Role Models*	5135	3	37	173	5348
		Average	101	6111	212	39	6463
		Reserved	0	76	3348	0	3424
		Self-Centered	140	110	0	4207	4457
	%	*Role Models*	96.0	0.1	0.7	3.2	100.0
		Average	1.6	94.6	3.3	0.6	100.0
		Reserved	0.0	2.2	97.8	0.0	100.0
		Self-Centered	3.1	2.5	0.0	94.4	100.0

a. 95.5% of original grouped cases correctly classified
Source: Own Calculation

4.3 MLP Neural Network

After identifying the four personality types, an MLP neural network was utilized as a predictive model to classify respondents based on their perceptions of the Big Five Personality Traits. The MLP Module of IBM SPSS Statistics 26 was employed as the tool for building and testing the accuracy of the the neural network model. This model was trained using the back-propagation learning algorithm, which uses gradient descent to update the weights and minimizes the error function (IBM, 2019).

Initially, the data was randomly assigned into training (70%) and testing (30%) subsets. The training dataset was used to determine the weights and construct the neural network model, while the testing data was used to assess errors and prevent overtraining. Out of the 19,692 data samples, 13,810 were allocated for training, and 5,882 were used for testing. The neural network model was built using the multilayer perceptron algorithm.

To identify the optimal MLP neural network, various network configurations were tested, leading to the conclusion that a single hidden layer MLP neural network was the best choice for this study. Sheela and Deepa (2013) emphasized that as the number of neurons or layers in a neural network increase, the training error also increases due to overfitting. Therefore, employing a single input layer, a single hidden layer, and a single output layer in the MLP neural network reduces the risk of overfitting and requires less computational time.

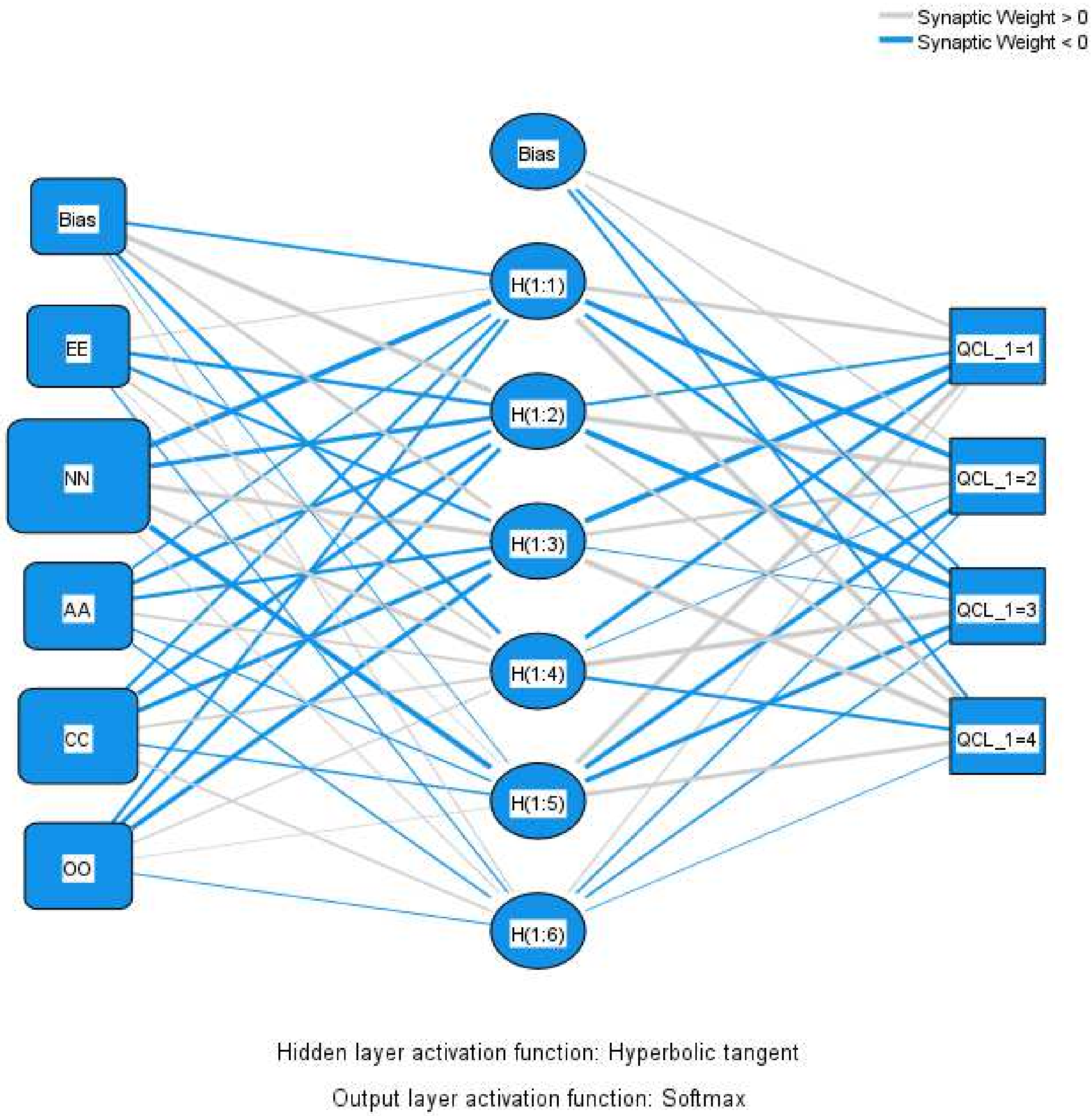

Figure 3. Network Diagram

Source: Own Calculation

The MLP Module of IBM SPSS Statistics 26 was used to automatically selected the best architecture model, resulting in a network with one hidden layer. The hyperbolic tangent function was chosen as the activation function for the hidden layer, while the softmax function was employed as the activation function for the output layer. Cross-entropy was utilized as error function due to the use of the softmax function. Intuitively, the cross-entropy loss function is employed to measure the error at a softmax layer, typically the final output layer in a neural network.

A crucial aspect in constructing a neural network is selecting differentiable activation functions for the hidden and output layers. The results of this study indicated that the hyperbolic tangent activation function can be used for the single hidden layer, as it cannot be effectively used in networks with multiple layers due to the vanishing gradient problem. Conversely, the rectified linear activation function can be employed for the output layer not only because it mitigates the vanishing gradient problem but also allows for faster learning and improved performance (Goodfellow et al., 2016).

Among the five independent variables in the input layer, the architecture automatically determined six nodes for the hidden layer, while the output layer had four nodes representing the dependent variable named “cluster,” which denoted the four identified personality types. The network diagram displayed the five input nodes, six hidden nodes, and four output nodes corresponding to the four personality types. From an architectural standpoint, it was a 5-6-4 neural network, signifying five independent (input) variables, six neurons in the hidden layer, and four dependent (output) variables (Figure 3).

The model summary, provided in Table 6, offers information regarding the results of the training and testing samples. The displayed cross-entropy error is associated with the softmax activation function, which serves as the error function for minimizing the network during the training phase (IBM, 2019). Both the training and testing samples are presented with their respective cross-entropy errors. The cross-entropy error value of 338.839 indicates the model's effectiveness in predicting the four identified personality types. Notably, the cross-entropy error was lower for the testing sample compared to the training dataset, indicating that the network model did not become overfitted to the training data and was able to generalize from trend. This outcome underscores the importance of the testing sample preventing overtraining.

In this study, the percentage of incorrect prediction was found to be only 0.6% in the training sample, resulting in a remarkable 99.4% correct prediction rate. Such accuracy is an excellent prediction in a qualitative study that aims to determine the results of the Big Five Personality Traits for the four identified personality types. The learning procedure was continued until a consecutive step was reached without any decrease in the error function from the training sample.

Table 6. Model Summary

Training	Cross Entropy Error	338.839
	Percent Incorrect Predictions	0.6%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:01.01
Testing	Cross Entropy Error	154.671
	Percent Incorrect Predictions	0.8%

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

Using only the training sample, the MLP neural network employed synaptic weights to represent the parameter estimates, illustrating the relationships between units in a given layer and the units in the subsequent layer (Table 7). It should be noted that the number of synaptic weights can become quite large, and that these weights are generally not utilized for interpreting network results (IBM, 2019).

Table 7. 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)**	**Cluster1**	**Cluster2**	**Cluster3**	**Cluster4**
Input Layer	**(Bias)**	-0.776	4.177	1.336	-1.470	-0.042	0.184				
	EE	0.155	-1.602	-1.059	0.411	0.021	-0.191				
	NN	-5.417	-2.547	3.487	2.070	-4.939	0.178				
	AA	-0.384	-1.734	-1.379	0.448	-0.211	-0.235				
	CC	-1.029	-2.338	-2.850	0.481	-0.258	0.378				
	OO	-1.172	-1.652	-3.336	0.228	0.026	-0.118				
Hidden Layer 1	(Bias)							0.912	0.279	-0.587	-0.810
	H(1:1)							2.291	-4.114	-1.640	4.218
	H(1:2)							-0.783	5.067	-5.110	1.320
	H(1:3)							-5.671	1.589	-0.065	4.969
	H(1:4)							-2.275	-0.058	4.302	-1.145
	H(1:5)							3.800	-3.144	-3.136	2.049
	H(1:6)							0.198	-0.301	-0.318	-0.040

Source: Own Calculation

Based on the MLP neural network, a predictive model was developed and presented a classification table, also known as a confusion matrix, for the categorical dependent variable representing the four identified personality types. This classification table included results for both partitioned and overall classifications (Table 8). As shown, the MLP neural network accurately classified 13,724 participants out of 13,810 in the training sample and 5,833 out of 5,882 in the testing sample. Overall, 99.4% of the training and 99.2% of the testing cases were correctly classified. The developed predictive model exhibited outstanding classification accuracy.

Using only the training sample, the model successfully classified 3,725 Role Models participants in the Role Models personality type out of 3,749. This yielded a classification accuracy of 99.4% for the Role Models personality type. Similarly, the model classified 4,516 Average participants in the Average personality type out of 4,541, as well as 2,396 Reserved participants in the Reserved personality type out of 2,412, and 3,087 Self-Centered participants in the Self-Centered personality type out of 3,108. The model achieved a classification accuracy of 99.4% for the Average personality type and 99.3% classification accuracy for both the Reserved and Self-Centered personality types.

Table 8. Predictive Ability and Classification Results

Classification						
Sample	**Observed**	**Predicted**				
		Role Models	***Average***	***Reserved***	***Self-Centered***	***Percent Correct***
Training	*Role Models*	3725	16	0	8	99.4%
	Average	15	4516	5	5	99.4%
	Reserved	5	11	2396	0	99.3%
	Self-Centered	7	14	0	3087	99.3%
	Overall Percent	27.2%	33.0%	17.4%	22.4%	99.4%
Testing	*Role Models*	1587	8	2	2	99.2%
	Average	8	1899	4	11	98.8%
	Reserved	2	7	1003	0	99.1%
	Self-Centered	1	4	0	1344	99.6%
	Overall Percent	27.2%	32.6%	17.2%	23.1%	99.2%

Dependent Variable: Cluster
Source: Own Calculation

The Receiving Operating Characteristic (ROC) curve is a widely used, two-dimension graph that measures the performance of classification problems. It is constructed by plotting the true positive rate (TPR) against the false positive rate (FPR). The true positive rate represents the proportion of correctly predicted positive observations out of all positive observations. Conversely, the false positive rate represents the proportion of incorrectly predicted positive observations out of all negative observations. For instance, in medical testing, the true positive rate reflects the rate at which individuals are correctly identified as testing positive for specific disease.

The ROC curve depicts sensitivity (or TPR) versus specificity (1 − FPR) and provides a visual representation of the classification performance for various cutoff points. When selecting a cutoff point, it is common to assign equal importance to sensitivity and specificity by choosing the point closest to the top-left corner of the ROC curve. As a reference, a random classifier would yield points along the diagonal (FPR = TPR). The closer the curve approaches the 45-degree diagonal line in the ROC space, the less accurate the test.

To assess and visualize the performance of the multi-class classification problem, the area under the ROC curve (AUC) is used a performance measure. It indicates the model's ability to distinguish between classes. Higher AUC values correspond to better separability in the model. A model with an AUC near one is considered excellent, indicating a high degree of separability. Conversely, a poor model would have an AUC near zero, suggesting the worst possible separability.

As depicted in Figure 4, the results of this study demonstrated excellent classification performance in distinguishing between personality types. Additionally, the AUC value was found to be 1.000, indicating that the classifier was able to perfectly distinguish between all positive and negative class points.

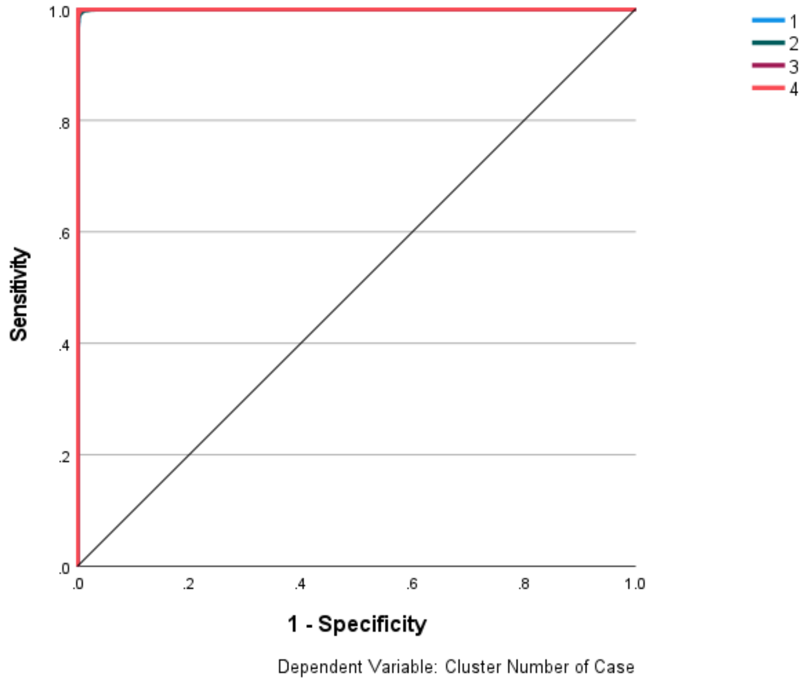

Figure 4. ROC Curve

Source: Own Calculation

The importance of individual independent variables, which are factor influencing personality types, is a measure of how much the predicted value of the network model changes for different independent variables (IBM, 2019). The neural network model ranked the input parameters, which are the Big Five personality traits influencing the four identified personality types, and the rankings are presented in Table 9. Therefore, analyzing the independent variable provides a level of sensitivity by determine the importance of each independent variable, which in turn influences the structure of the neural network.

The most significant dominant factors found was "Neuroticism" (100%), which had the greatest contribution to the construction of the neural network model. It was followed by "Conscientiousness" (75.5%) and "Agreeableness" (64.4%), which also had a substantial effect on participants' perceptions in terms of the Big Five Personality Traits. The next important factor was "Openness to Experience" (63.7%), while the least important factor identified was "Extraversion" (57.7%).

Table 9. Independent Variable Importance Analysis

	Importance	Normalized Importance	Rank
Extraversion	0.160	57.7%	5
Neuroticism	0.277	100.0%	1
Agreeableness	0.178	64.4%	3
Conscientiousness	0.209	75.5%	2
Openness to Experience	0.176	63.7%	4

Source: Own Calculation

The independent variable importance chart displayed the impact of each independent variable in the MLP neural network model in terms of relative and normalized importance (IBM, 2019). Additionally, the chart illustrated the importance of the independent variables and how sensitive the model is to changes in each input variable (Figure 5).

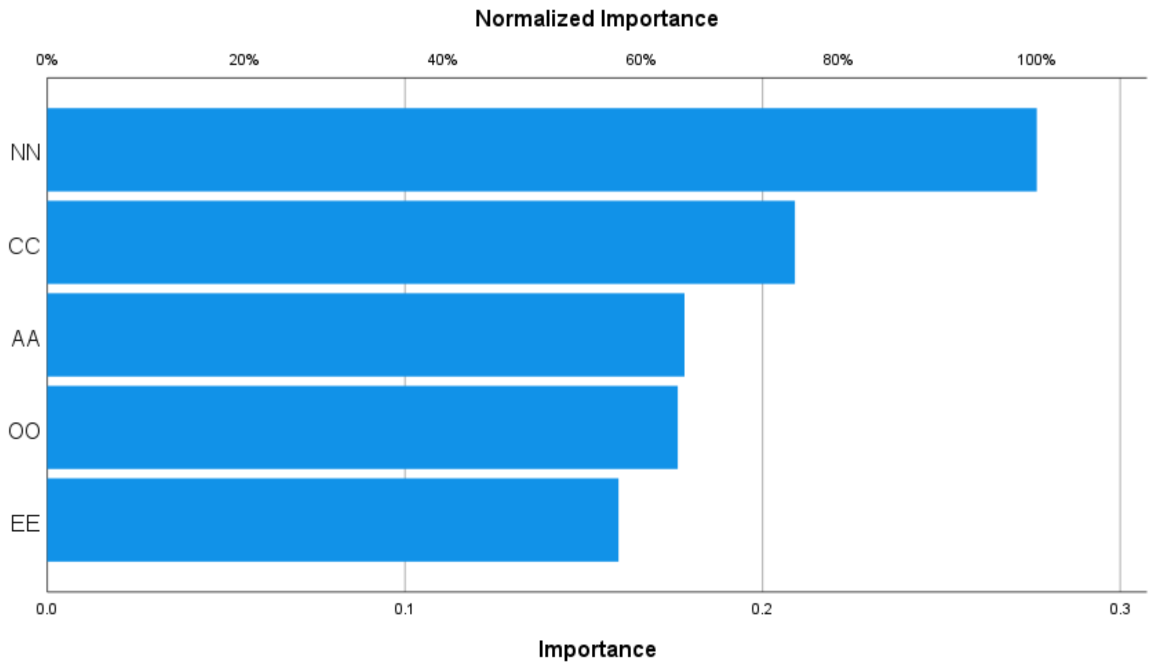

Figure 5. Independent Variable Importance Chart

Source: Own Calculation

4.4 Profile Analysis

Once the four personality types were identified, a series of statistical tests were conducted to investigate the relationship between these personality types and various demographic factors, including age, gender, race, English (native language), hand preference (writing hand), and the source of participation in the test. To examine the significant differences between male and female respondents across the four identified personality types, the Chi-square test was employed. The results revealed significant gender differences among the four personality types ($\chi 2 = 274.161$; $df = 9$; $p < 0.001$) at a significance level of 0.01 (Table 10).

Table 10. Gender Composition of the Identified Personality Types

Gender		*Role Models*	*Average*	*Reserved*	*Self-Centered*	Total
0=missed	Count	6	6	1	11	24
	% within Gender	25%	25%	4.2%	45.8%	100%
	% within Cluster	0.1%	0.1%	0.0%	0.2%	0.1%
1=Male	Count	2447	2127	1168	1851	7593
	% within Gender	32.2%	28.0%	15.4%	24.4%	100%
	% within Cluster	45.8%	32.9%	34.1%	41.5%	38.6%
2=Female	Count	2872	4278	2242	2584	11976
	% within Gender	24.0%	35.7%	18.7%	21.6%	100%
	% within Cluster	53.7%	66.2%	65.5%	58.0%	60.8%
3=Other	Count	23	52	13	11	99

	% within Gender	23.2%	52.5%	13.1%	11.1%	100%
	% within Cluster	0.4%	0.8%	0.4%	0.2%	0.5%
Total		5348	6463	3424	4457	19692

*1 cells (6.3%) have expected count less than 5. The minimum expected count is 4.17.
Source: Own Calculation

The composition of race among the four identified personality types exhibited significant differences ($\chi2 = 387.694$; df = 39; $p < 0.001$), as determined by the Chi-square test (Table 11).

Table 11. Race Composition of the Identified Personality Types

Race	*Role Models*	*Average*	*Reserved*	*Self-Centered*	Total
0	31	60	23	38	152 (0.8%)
1	398	459	261	315	1433 (7.3%)
2	6	0	3	3	12 (0.1%)
3	3170	3533	1465	2361	10529 (53.5%)
4	286	490	404	334	1514 (7.7%)
5	115	173	107	118	513 (2.6%)
6	117	135	67	78	397 (2.0%)
7	6	5	7	5	23 (0.1%)
8	55	61	34	51	201 (1.0%)
9	45	56	44	42	187 (0.9%)
10	19	19	9	17	64 (0.3%)
11	357	658	436	409	1860 (9.4%)
12	91	53	47	68	259 (1.3%)
13	652	761	517	618	2548 (12.9%)
Total	5348	6463	3424	4457	19692

*5 cells (8.9%) have expected count less than 5. The minimum expected count is 2.09.
Source: Own Calculation

Among the four identified personality types, significant differences were found between English-speaking and non-English-speaking respondents as indicated by the Chi-square test ($\chi2 = 153.955$; df = 6; $p < 0.001$) at a significance level of 0.01 (Table 12).

Table 12. English (Native Language) Composition of the Identified Personality Types

English		*Role Models*	*Average*	*Reserved*	*Self-Centered*	Total
0=missed	Count	19	23	10	18	70
	% within English	27.1%	32.9%	14.3%	25.7%	100%
	% within Cluster	0.4%	0.4%	0.3%	0.4%	0.4%
1=Yes	Count	3674	3967	1920	2805	12366
	% within English	29.7%	32.1%	15.5%	22.7%	100%
	% within Cluster	68.7%	61.4%	56.1%	62.9%	62.8%
2=No	Count	1655	2473	1494	1634	7256
	% within English	22.8%	34.1%	20.6%	22.5%	100%
	% within Cluster	30.9%	38.3%	43.6%	36.7%	36.8%
Total		5348	6463	3424	4457	19692

*0 cells (0.0%) have expected count less than 5. The minimum expected count is 12.17.
Source: Own Calculation

Likewise, there were significant differences between right-hand-writing and left-hand-writing respondents among the four identified personality types, based on the Chi-square test ($\chi2 = 38.324$; df = 9; $p < 0.001$) at 0.01 level of significance (Table 13).

Table 13. Hand-Writing Composition of the Identified Personality Types

Hand		*Role Models*	*Average*	*Reserved*	*Self-Centered*	Total
0=missed	Count	31	28	18	23	100
	% within Hand	31.0%	28.0%	18.0%	23.0%	100%
	% within Cluster	0.6%	0.4%	0.5%	0.5%	0.5%
1=Right	Count	4687	5737	2998	3981	17403
	% within Hand	26.9%	33.0%	17.2%	22.9%	100%
	% within Cluster	87.6%	88.8%	87.6%	89.3%	88.4%
2=Left	Count	459	582	309	372	1722
	% within Hand	26.7%	33.8%	17.9%	21.6%	100%
	% within Cluster	8.6%	9.0%	9.0%	8.3%	8.7%
3=Both	Count	171	116	99	81	467
	% within Hand	36.6%	24.8%	21.2%	17.3%	100%
	% within Cluster	3.2%	1.8%	2.9%	1.8%	2.4%
Total		5348	6463	3424	4457	19692

*0 cells (0.0%) have expected count less than 5. The minimum expected count is 17.39.
Source: Own Calculation

Furthermore, the Chi-square test revealed significant differences in respondent source composition among the four identified personality types ($\chi2 = 223.897$; df = 12; $p < 0.001$) at a significance level of 0.01 (Table 14).

Table 14. Source Composition of the Personality Type-Clusters

Source		*Role Models*	*Average*	*Reserved*	*Self-Centered*	Total
1	Count	2948	4214	2316	2608	12086
	% within Source	24.4%	34.9%	19.2%	21.6%	100%
	% within Cluster	55.1%	65.2%	67.6%	58.5%	61.4%
2	Count	1223	1061	498	862	3644
	% within Source	33.6%	29.1%	13.7%	23.7%	100%
	% within Cluster	22.9%	16.4%	14.5%	19.3%	18.5%
3	Count	96	96	38	73	303
	% within Source	31.7%	31.7%	12.5%	24.1%	100%
	% within Cluster	1.8%	1.5%	1.1%	1.6%	1.5%
4	Count	33	48	28	28	137
	% within Source	24.1%	35.0%	20.4%	20.4%	100%
	% within Cluster	0.6%	0.7%	0.8%	0.6%	0.7%
5	Count	1048	1044	544	886	3522

	% within Source	29.8%	29.6%	15.4%	25.2%	100%
	% within Cluster	19.6%	16.2%	15.9%	19.9%	17.9%
Total		5348	6463	3424	4457	19692

*0 cells (0.0%) have expected count less than 5. The minimum expected count is 23.82.
Source: Own Calculation

In statistics, one-way ANOVA is a technique used to compares the means of two or more independent groups using the F distribution. Its purpose is to determine whether there is statistical evidence supporting significant differences among the associated population means. Thus, a one-way ANOVA was conducted to investigate the effects of respondents' age on the four identified personality types. The results revealed significant differences among the four personality types with respect to age ($F(3, 19688) = 190.208$, $p < 0.001$) at a significance level of 0.01 (Table 15).

Table 15. Age Composition of the Identified Personality Types

Age	***Role Models***		***Average***		***Reserved***		***Self-Centered***		**Total**	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
	28.96	12.84	24.65	10.43	24.10	9.89	26.96	11.91	26.25	11.55

Source: Own Calculation

Additionally, a one-way ANOVA was performed to examine the effects of the Big Five Personality Traits on the four identified personality types. The results indicated significant differences among the four personality types in relation to the Big Five Personality Traits (Table 16). Specifically, significant differences were observed for "EE" ($F(3, 19688) = 850.661$, $p < 0.001$), "NN" ($F(3, 19688) = 15412.022$, $p < 0.001$), "AA" ($F(3, 19688) = 1400.584$, $p < 0.001$), "CC" ($F(3, 19688) = 2818.831$, $p < 0.001$), and "OO" ($F(3, 19688) = 2395.272$, $p < 0.001$) respectively.

Table 16. One-Way ANOVA the Identified Personality Types with the Big Five Personality Traits

		df	***F***	***P***
EE	Between Groups	3	850.661	0.000
	Within Groups	19688		
NN	Between Groups	3	15412.022	0.000
	Within Groups	19688		
AA	Between Groups	3	1400.584	0.000
	Within Groups	19688		
CC	Between Groups	3	2818.831	0.000
	Within Groups	19688		
OO	Between Groups	3	2395.272	0.000
	Within Groups	19688		

Source: Own Calculation

4.5 Multinomial Logistic Regression Analysis

Once the four personality types have been identified, a multinomial logistic regression analysis (MLR) is conducted to examine the relationship between selected variables and memberships in these personality types. The dependent variable in this study represents the four personality types, assigned with the values: 1 = Role Models personality type, 2 = Average personality type, 3 = Reserved personality type, and 4 = Self-Centered personality type. The explanatory variables considered in the model include age, gender, race, English proficiency (as a native language), hand-writing preference, and information source. Empirically, the multinomial logit regression (MLR) model in this study can be expressed as follows:

$$Log\left(\frac{Prob(Y_i=j)}{Prob(Y_i=j')}\right) = \alpha + \beta_1(age) + \beta_2(gender) + \beta_3(race) + \beta_4(English) + \beta_5(hand\ writing) + \beta_6(source) \quad (3)$$

Here, j represents the identified personality type (*Role Models, Reserved,* and *Self-Centered*), while j' represents the reference personality type (*Average*).

Table 17 presents the identified personality types for the multinomial logit model, with the *Average* personality type serving as the reference category. It is compared separately to the *Role Models, Reserved,* and *Self-Centered* personality types, with distinct parameter estimates. This feature of the MLR is one of its main strengths, as it allows for the computation of different estimates for each paired groupings of the dependent variable. This enables the identification of different effects of specific variable within each group (Greene, 2008).

The results revealed that the *Role Models* personality type and *Average* personality type differed significantly across five variables: age, gender, English proficiency, and information source at the 1% level, and hand-writing preference at the 5% level. However, there was no significant difference between the two personality types in terms of the “race” variable. The positive sign for the “age” variable indicates that participants are more likely to belong to the *Role Models* personality type. Conversely, the negative sign for the “gender” variable suggests that participants are less likely to belong to the *Role Models* personality type due to gender differences.

Similarly, the *Reserved* personality type and *Average* personality type differed significantly across four variables: race, English proficiency, and hand-writing preference at the 1% level, and age at the 5% level. However, there was no significant difference between the two personality types regarding the “gender” and “information source” variables. Participants were more likely to belong to the *Reserved* personality type based on difference in English speaking, as indicated by the positive sign for the “English” variable. Additionally, participants were less likely to belong to the *Reserved* personality type compared to the *Average* personality type in relation to difference among information sources, as suggested by the negative sign for the “source” variable.

Furthermore, the *Self-Centered* personality type and *Average* personality type exhibited significant differences across five variables: age, gender, race, and information source at the 1% level, and English proficiency at the 5% level. However, there was no significant difference between these two personality types in terms of the “hand-writing preference” variable. The positive sign for the “race” variable indicates that participants are more likely to belong to the *Self-Centered* personality type compared to the *Averaged* personality type based on race differences. Conversely, the negative sign for the “English” variable suggest that participants are less likely to belong to the *Self-Centered* personality type due to differences in English speaking.

Table 17. Parameter Estimates for the Multinomial Logit Model

	Coefficient	**Standard Error**	**z**	**P > |z|**
***Role Models* Personality Type**				
Intercept	-0.1067	0.1187	-0.90	0.369
Age	0.0316	0.0017	19.10	0.000
Gender	-0.5714	0.0382	-14.97	0.000
Race	0.0060	0.0049	1.22	0.222
English	-0.2820	0.0406	-6.94	0.000
Hand-Writing	0.1157	0.0454	2.55	0.011
Source	0.1087	0.0126	8.63	0.000
***Reserved* Personality Type**				
Intercept	-0.9592	0.1372	-6.99	0.000
Age	-0.0044	0.0022	-2.03	0.042
Gender	-0.0653	0.0438	-1.49	0.136
Race	0.0350	0.0053	6.65	0.000
English	0.1529	0.0442	3.46	0.001
Hand-Writing	0.1383	0.0505	2.74	0.006
Source	-0.0134	0.0150	-0.89	0.372
***Self-Centered* Personality Type**				
Intercept	-0.3365	0.1254	-2.68	0.007
Age	0.0199	0.0018	11.15	0.000

Gender	-0.4107	0.0399	-10.30	0.000
Race	0.0210	0.0050	4.19	0.000
English	-0.0894	0.0416	-2.15	0.032
Hand-Writing	-0.0415	0.0498	-0.83	0.405
Source	0.0918	0.0131	6.99	0.000
# of Observations = 19692	Log Likelihood = -26222.188	LR Chi^2 (18) = 1122.62	Prob > Chi^2 = 0.0000	Pseudo R^2 = 0.0210

* The Reference Category: *Average* Personality Type
Source: Own Calculation

5. Conclusion

Understanding human personality can help us recognize how people will respond to certain situations and understand their preferences and values in terms of individual differences in thinking, feeling, and behavior. There are various approaches that can be used to identify one's personality type, such as the Big Five Personality Traits. This understanding of personality types can be valuable in business settings, informing us on how we lead, influence, communicate, collaborate, negotiate, and manage stress.

This study offered a mixed model approach, combining k-means clustering analysis for data examination, discriminant analysis for classification, and a multilayer perceptron neural network for prediction. Overall, the study utilized k-means clustering analysis to identify four personality types: Role Model personality type (27.2% of 19692 respondents), Average personality type (32.8%), Reserved personality type (17.4%), and Self-Centered personality type (22.6%).

Average individuals exhibit high neuroticism and below-average extraversion, agreeableness, conscientiousness and openness to experience. Role Models possess high levels of extraversion, agreeableness, conscientiousness and openness to experience, with relatively low levels of neuroticism. Self-Centered people are below average on all five traits, especially low on neuroticism. Reserved individuals are above average on all five traits, particularly high on neuroticism.

Theoretically, a cluster is a collection of similar items that differ from items in other clusters. There is no universally optimal criterion independent of the clustering's ultimate purpose. Therefore, the user must determine the cluster structure based on specific requirements. Thus, there is no definitive approach to correctly classify participants based on their Big Five Personality Traits.

The classification results from discriminant analysis showed that 95.5% of original grouped cases were correctly classified. After forming the four identified clusters, an MLP neural network model was utilized to predict model the classifications of respondents based on their Big Five Personality Traits. The model achieved a 99.4% correct classification rate for training cases, indicating excellent accuracy.

The MLP neural network is widely recognized as an efficient approach for adaptive pattern classification. In this study, efforts were made to enhance the learning capabilities of an MLP neural network and reduce the time and resources required for the learning process. The multilayer perceptron neural network model served as a predictive model for classifying respondents based on their Big Five Personality Traits. The results indicated a 5-6-4 neural network structure from an architectural standpoint, highlighting neuroticism and conscientiousness most influential factors in respondents' perception of the Big Five Personality Traits.

The main finding of the study was that the four identified personality types differed in terms of age, gender, race, English-speaking versus non-English-speaking, right-hand-writing versus left-hand-writing, information source, and the Big Five Personality Traits. Given the nature of the dataset, the study's results can serve as a reference for human personality classification. However, it is important for future research to consider including socio-economic characteristics of participants, such as age, cohort, gender, and its business-centric applications, to address the study's main limitations.

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