Psikiyatride Güncel Yaklaşımlar-Current Approaches in Psychiatry 2019; 11(Suppl 1):64-78
doi: 10.18863/pgy.554788

RESEARCH

Prediction of the Level of Alexithymia through Machine Learning Methods Applied to Automatic Thoughts

Otomatik Düşüncelere Makine Öğrenme Yöntemlerinin Uygulanması ile Aleksitimi Düzeyinin Tahmini

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Abstract

This study aims to investigate the relationship among alexithymia levels and automatic thoughts from cognitive behavioral therapy concepts. For this aim, Fisher Score analysis was applied to determine the most effective attributes of the automatic thoughts scale. In addition, the level of alexithymia was predicted by the introduction of the data set into the machine learning methods of the Artificial Neural Network (ANN) and Support Vector Machine (SVM). It is aimed to develop a roadmap of what automatic thoughts should be given priorities in studies. The research, from 10 different provinces of Turkey, was performed with a total of 714 participants, of which 386 (54%) male and 328 (46%) female. Personal information form, Automatic Thoughts Scale and Toronto Alexithymia scale were applied to the participants. The data set obtained from the scale of automatic thoughts was applied to the feature selection by using the Fisher Score method and a data set containing 5 attributes was obtained. As a result of the implementation of the SVM method to this data set, the alexithymia level was predicted with 4.01 RMSE error. The results show that the features of the automatic thoughts are related to the alexithymia level.

Keywords*:* Alexithymia, automatic thoughts, machine learning.

Öz

Bu araştırmada bilişsel davranışçı terapi kavramlarından otomatik düşüncelerin aleksitimi ile ilişkisi incelenmiştir. Bu amaçla otomatik düşünceler ölçeğini oluşturan en etkili öznitelikleri tespit etmek için FisherScore analizi uygulanmıştır. Ayrıca veri kümesinin Yapay Sinir Ağı (YSA) ve Destek Vektör Makinesi (DVM) makine öğrenmesi yöntemlerine giriş olarak verilmesiyle aleksitimi düzeyi tahmin edilmiş ve bu sayede önceliğin hangi otomatik düşüncelere vermesi gerektiği konusunda bir yol haritası sunulması amaçlanmıştır. Araştırma Türkiye'nin 10 farklı ilinden 386 (%54) erkek 328 (%46) kadın olmak üzere 714 katılımcı ile gerçekleştirilmiştir. Katılımcılara kişisel bilgiler formu, Otomatik Düşünceler Ölçeği ve Toronto Aleksitimi ölçeği uygulanmıştır. Otomatik düşünceler ölçeğinden elde edilen veri kümesine Fisher Score yöntemi ile öznitelik seçim işlemi uygulanarak 5 adet öznitelik içeren veri kümesi elde edilmiştir. Bu veri kümesine DVM yönteminin uygulanması sonucunda 4.01 RMSE hatası ile aleksitimi seviyesi tahmin edilmiştir. Sonuçlar otomatik düşünceler ölçeğindeki özniteliklerin aleksitimi düzeyi ile ilişkili olduğunu göstermektedir.

Anahtar sözcükler: Aleksitimi, otomatik düşünce, makine öğrenmesi.

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Submission date: 17.04.2019 | Accepted: 14.05.2019 | Online published: 27.05.2019

ALEXITHYMIA could shortly be defined as emotional blindness (Grabe et al. 2004). It is stated that the person showing alexithymic features has difficulties in understanding and regulating their feelings (Nemiah et al. 1970, Motan et al. 2007). When examined the researches related to alexithymia, it is seen that studies mostly investigate the relationship between alexithymia and various psychiatric disorders in general (Honkalampi et al. 2000, Berthoz et al. 2007, Declercq et al. 2010, Coriale et al. 2012, Coolidge et al. 2013). In other words, alexithymia is a problem associated with other psychiatric disorders rather than a different disorder (Solmaz et al. 2000). Although there are various theoretical perspectives in the explanation of alexithymia (Stephanos 1975, Wolff 1977, Levant 1992), cognitive-behavioral therapies are among the most preferred models by experts in the field.

According to the cognitive perspective, cognition is an important factor that lies at the heart of emotional disorders (Stoudemire 1991). Beck (1979), the founder of cognitive therapy, emphasizes the priority importance of cognition in the treatment of psychological problems. In other words, cognition leads to the formation of emotions and behaviors. In this regard, Lazarus (1982) has described the emotions as a consequence of the cognitive evaluations of the individual during the interaction with the environment, and argued that cognitive evaluations are what lies under the emotions. Martin and Phil (1986) described alexithymia based on Lazarus' view and argued that individuals with alexithymia are unable to complete their cognitive development. According to them, individuals with alexithymia use primitive cognitive schemas. Martin and Phil (1986) also argued that cognitive distortions and assumptions may also lead to alexithymia since they are the premise of emotions. And, this suggests that alexithymia, which is associated with the emotions of the individual, may have a cognitive priority.

The most observable structure of cognitive communication is the automatic thoughts. Automatic thoughts come to the minds of individuals in an involuntary, unplanned way. Automatic thoughts emerge as a response to the environment and situation, usually in the form of emotional responses (Greenberger et al. 2015). Automatic thoughts arise spontaneously, and usually the individuals cannot notice them. The emotions that emerge as a result of automatic thoughts are what the individuals recognize. These emotions are parallel to the content of automatic thoughts (Türkçapar 2007). Beck (2000) had stated that automatic thoughts are spontaneously and quickly emerging thoughts come to the mind, and reinforce the negative feelings (Şahin 2017). Automatic thoughts emerge suddenly and they cannot be controlled. Since they emerge very quickly, they are considered correct without passing thought a rationality filter. Automatic thoughts are logical and convincing for the individual (Beck 2001). It has been stated that the automatic thoughts lie at the basis of emotions such as hopelessness, depression, anxiety and anger (Beck 2001). Events that occur during early childhood contribute to the formation of basic thoughts and beliefs. These basic thoughts and beliefs that arise in the early period shape the self-perception and world view of the individuals. These basic thoughts and beliefs surface in a particular life event, revealing automatic thoughts. Automatic thoughts emerge as a result of cognitive errors and distortions that occur during the processing of data related to a particular event (Schniering et al. 2002). In summary, automatic thoughts can be described as suddenly emerging thoughts that have reflections of cognitive schemas at their origin, which can be discovered more easily than the schemas. For this reason, in the cognitive-behavioral therapy (CBT) procedure, firstly, the automatic thoughts of the clients are revealed to reach the cognitive schemas. In other words, automatic thoughts are considered first, when performing the client's case formulation. According to the studies conducted on different clinical samples on the effect of CBT on alexithymia level, CBT-based therapies have positive effects on alexithymia levels (Bach et al. 1995, Rosenblum et al. 2005, Ruffer et al. 2008, Spek et al. 2008). In this study, it is tried to find out which automatic thoughts which are an important element of CBT are predictive of alexithymia. In this way, a road map has been tried to be prepared on which automatic thoughts should be addressed by field employees in CBT based therapies.

Although there are numerous different estimation methods and analysis in statistics, the method known as machine learning is used to reveal previously unknown and potentially useful information. It is seen that numerous machine learning methods such as classification, estimation and clustering are used in many studies in the field of psychology (Baba-Garcia et al. 2006, Song 2010, Qinghua 2016).

Using machine learning methods, Baca-Garcia et al. (2006) have suggested the hospitalization decisions of psychiatrists in 509 suicide committers taken under control in the emergency department. According to the results of the study, patients have been correctly classified by a 99% success rate using the Forward Selection method. Nguyen et al. (2010) have investigated machine learning methods to evaluate the results of insomnia symptoms in the treatment of long-term sleep apnea syndrome. They have showed using decision trees the negative responses to treatment have not been related to long-term adjustment studies. Song (2010) has used kNN, Bayes and SVM machine learning method in order to investigate the psychological evaluation data of college students. The best result was reached for the binary classification model was achieved by using SVM with a success rate of 79.1%. Qinghua (2016) has applied machine learning technology based on the back-propagated artificial neural network to enhance the operational efficiency of the students in psychological data management system. The study has aimed to prevent psychological crises in particular. Rosenthal et al. (2007) have used machine learning methods to examine the factors affecting professional outcomes in the occupational rehabilitation process of people with psychiatric disorders who received occupational rehabilitation services. With the help of the CHAID algorithm, it has been shown that there is a positive effect on professional outcomes for people receiving job placement services. Bae et al. (2010) have used decision tree algorithms to examine the variables that have a significant effect on patients with schizophrenia in terms of good social functionality. As it can be seen, machine learning is being used in the fields of psychology. The aim of this study is to investigate the relationship among alexithymia levels and automatic thoughts from cognitive behavioral therapy concepts. For this aim, Fisher Score analysis was applied to determine the most effective attributes of the automatic thoughts scale. In addition, the level of alexithymia was predicted by the introduction of the data set into the machine learning methods of the Artificial Neural Network (ANN) and Support Vector Machine (SVM). Thus, it was aimed to form a resource for future studies.

Method

Sample

The study group consisted of 714 participants, of which 386 (54%) were male and 328

(46%) were female. The age of the participants varies between 16 and 40 (=21.84, Standard Deviation=3.68). Of the participants, 129 (18.07%) were graduates, 495 (69.32%) were university students and 90 (12.60%) were high school graduates. Participants have been involved in the research from 10 different provinces of Turkey. These provinces were Istanbul (n = 94), Ankara (n = 106), Diyarbakır (n = 38), Malatya (n = 47), Izmir (n = 64), Antalya (n = 24), Adana (n = 51). , Tokat (n = 130), Nevşehir (n = 141), Erzincan (n = 19). The appropriate sampling method was used in the study and the participants were selected as non-clinical sample. Before the scales were applied, the participants were informed about the research and it was stated that it was the volunteer basis for participation in the research. Then, informed consent form (n = 495) was obtained from the participants. In the data collected thought the Google Drive (n = 219), a text explaining the research topic was given first and each participant was asked to give consent for participation in the study..

Measures

Personal Information Form, Toronto Alexithymia Scale and Automated Thoughts Questionnaire scales have been used to collect research data. The reason why Toronto Alexithymia Scale and Automated Thoughts Questionnaire were selected within the scope of the research widespread use of these scales in the literature and psychometric properties of the scale is sufficient in the researches (Şahin et al. 1992, Motan et al. 2007, Güleç et al. 2009, Güleç et al. 2010, Oktay et al. 2014, Arcan et al. 2016, Karahan et al. 2016).

Personal Information Form

In the personal information forms, information such as the gender of the participants, the province where they live and their education level were collected.

Toronto Alexithymia Scale

The 5-point Likert-type Toronto Alexithymia Scale (TAS-20), developed by Bagby et al. and adapted to Turkish by Gulec et al., evaluates extroverted-thinking dimensions in addition to difficulties in recognizing and expressing emotions (Bagby et al. 1994, Güleç et al. 2009). The score that can be taken from the scale ranged from 20 to 100 points and the Cronbach's alpha internal consistency coefficient of the Turkish version has been reported as .78 for the total scale (Güleç et al. 2009). The Cronbach's alpha internal consistency coefficient for the entire scale in this study was calculated as .72.

Automated Thoughts Questionnaire

Developed by Hollan and Kendall, the Automatic Thoughts Scale (ATQ) is a 5-point Likert-type scale (Hollan et al. 1980). The scores taken in the scale are in the range of 30-150. Cronbach's Alpha internal consistency coefficient of its Turkish version has been found to be .93 (Şahin et al. 1992). In this study, the Cronbach's alpha internal consistency coefficient for the entire scale was .96. And, the Cronbach's alpha internal consistency coefficients for the sub-scales were as follows: .91 for "self-concept", .86 for "confusion and escape fantasies", .66 for "personal maladjustment and desire for change", .80 for "loneliness/isolation" and .87 for "giving up/helplessness"..

Statistical Analysis

For the analysis, Fisher artificial neural network (ANN) with score feature selection method and support vector machine (SVM) prediction methods were used. Experimental analyzes were performed on Matlab R2017b and Weka platforms. All three are the methods used in medical and psychological studies in recent years (Bilge 2007, Ghazavi et al. 2008, Yavuz et al. 2011). The Fisher Score method for feature selection and the ANN and SVM methods for the prediction in the study were used because of their higher success rates and time performance (Öztürk 2008, Ayhan et al. 2014). Brief information about Fisher Score, ANN and SVM methods are as follows:

Fisher Scoring Method

This feature selection method is often used as a pre-processing step in the machine learning. The feature selection process provides significant benefits in terms of time complexity and eliminating noisy features (Cai et al. 2009). One of the methods used for feature selection process is filtering methods based on statistical information. In these methods, feature selection based on statistical criteria is performed. For each feature in the study data set, the score values are calculated using the statistical objective functions and the effect of the features are ordered according to these values in these filtering methods (Hsu et al. 2011). Fisher score method, which is one of the most used filtering methods, was used in the study. This method calculates a correlation score as in Equation 1 using mean and standard deviation values, which are among the most common statistical measures, for features in each class (Ferreira et al. 2012).

$$FS(x_i) = \frac{|\mu_i^+ - \mu_i^-|}{\sigma_i^+ - \sigma_i^-} \tag{1}$$

The symbols + and - in Equation 1 refer to two different classes. μi is the arithmetic average of each class, and σi is the standard deviation of each class. The Fisher score method is used for feature selection by picking up the desired number of features starting with the upper ranks, after sorting the features according to the calculated score values (Saeys et al. 2007).

Artificial Neural Network

Artificial Neural Network (ANN) is a method of estimating processes that produce results on new samples encountered by interpreting known causes and outcomes (Haykin 1999). In this study, Multilayer Perceptron Neural Network (MLPNN) model was used as the artificial neural network model (Öztürk 2008). This model consists of 3 layers: input, hidden and output. The hidden layer contains neurons with activation function. Figure 1 shows a sample neuron used in MLPNN.

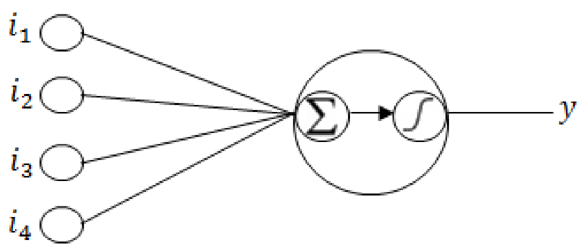

Figure 1. A sample neuron used in MLPNN

As shown in Figure 1, each dimension (i1, i2, i3, ..., in) of the data is multiplied by a separate weight (w1, w2, w3, ..., wn), and the inputs pass thought two processing units in the neuron and the obtained value is transferred to the output (y). The first processing unit is a linear unit that multiplies each incoming data by weights and sums up the results. Then, this result is sent to a second unit containing the activation function. The value passed thought the activation function is then transferred to the output layer. The equations used in the hidden layer are given in Equations 2 and 3.

$$n = \sum_k i_k w_k \quad (2)$$

$$y_{out} = g(n) \quad (3)$$

The expression g in Equation 3 shows the activation functions. Hyperbolic tangent, sigmoid and unit step functions are usually used in the studies (Demuth et al. 2000).The activation functions have advantages over each other according to the problem encountered.

In MLPNN, a variety of back-propagation training algorithms are used that optimize the output of the network by adjusting the weights of the connections between the neurons (Hagan et al. 1994). In this way, the difference between real value (y) and the value at the output of the network (y') is found and the weights of all connections are updated according to the calculated values. The gradient reduction method is usually used in the update phase (Kaastra et al. 1996). The equations used for performing these operations are given in Equations 4, 5 and 6..

$$e = y' - y \quad (4)$$

$$\varepsilon = \frac{1}{2} e^2 \quad (5)$$

$$\Delta w = -\eta \frac{\delta \varepsilon}{\delta w} \quad (6)$$

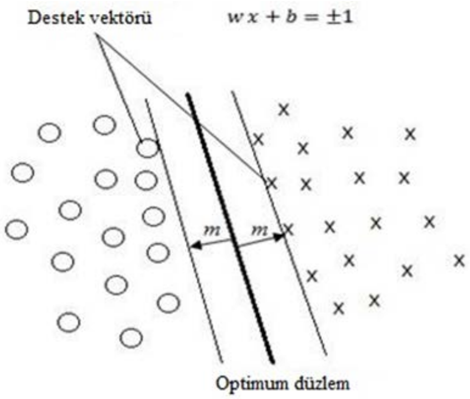

Figure 2. Optimum plane and support vectors (Vapnik et al. 2000)

Equation 4 calculates the value of e, which shows the deviation between the real value and the value calculated by the network. Equation 5 calculates the instantaneous error energy of the neuron (ε). In Equation 6, the update amount of each weight (Δw) is calculated by distributing the calculated error energy to all the connection weights incoming to the corresponding neuron in an inversely proportional to the current weights (w) (Kaastra et al. 1996, Nabiyev 2003). The averages of the solutions are calculated by performing calculations separately for each sample in the dataset.

Support Vector Machine (SVM)

Support vector machine (SVM) is a classifier based on statistical learning theory (Vapnik et al. 2000).The purpose of the SVM is to predict the most appropriate decision function that can distinguish between the two classes (Hearst et al. 1998, Vapnik et al. 2000). With this decision function, the most suitable hyperplane is determined which can distinguish the training data set as shown in Figure 2.

Equations for the support vectors in SVM are given in Equation 7 to be used in a binary classification problem that can be differentiated linearly.

$$wx + b = +1 \text{ için} \qquad y = +1 \text{ sınıfı} \tag{7}$$

$$wx + b = -1 \text{ için} \qquad y = -1 \text{ sınıfı}$$

Where y is the class label, w is the weight vector, and b is the value of approximation. To increase the optimum plane spacing, it is necessary to minimize the value of w as shown in Equation 7 (Hastie et al. 2009).

$$m = \frac{2}{\sqrt{ww}} \quad f_{min}(w) = \frac{ww}{2} \tag{8}$$

Based on Equation 8,

$$y_i(wx_i + b) - 1 \geq 0 \tag{9}$$

is obtained. The solution of Equation 9 with Lagrange equations gives Equation 10.

$$L(w, b, a) = \frac{w^2}{2} - \sum_{i=1}^{k} a_i y_i (wx_i + b) + \sum_{i=1}^{k} a_i \tag{10}$$

The decision function of the support vector machine for a two-class problem is given in Equation 11 (Osuna et al. 1997).

$$\mathrm{f(x)} = \mathrm{sign}(\textstyle\sum_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{a_i y_i (x_i)} + \mathrm{b}) \tag{11}$$

The a_i and y_i parameters found in Equation 10 are the regulatory parameters that adjust the margin width. The smaller the parameter values, the easier it is to ignore the constraints that cause the large margin range. If the values are large, it makes it difficult to ignore the constraints that cause the small margin range (Pardo et al. 2005). Therefore, as a result of experimental studies, it is very important to adjust the parameters to make the classification the best. The most important advantage of the SVM is that it reduces the number of processes in the training phase by transforming the prediction problem into a square optimization problem and finds the result faster than other algorithms at this stage (Nitze et al. 2012). Moreover, since it is optimization based, it performs better than other methods in terms of prediction accuracy and computational complexity in large data sets (Vapnik et al. 2000).

Traditional statistical analyzes assume a linear relationship between independent and dependent variables. This is an important mistake. Past research shows that relationships are generally not linear (Garver 2002). The most important advantage of Artificial Neural Networks is their ability to learn from their previous experiences, the ability to intelligently identify unknown relationships by means of data sets, and to adapt itself to the solution of a concrete problem when their parameters such as network weight coefficient and structure change. In addition, non-linear functions to the solution go. Therefore, complex statistical problems can solve problems more accurately. Nonlinear behavior is felt, sensed and known. However, it is difficult to solve these problems and behaviors mathematically (Güneri 2001, Elmas 2003). The main advantage of Support Vector Machines is that it converts the classification problem into a squared optimization problem. Thus, the number of transactions decreases in the training phase of the problem solving process and a faster solution than other techniques / algorithms (Osowski et al. 2004). In addition, because it is optimization-based, classification performance, computational complexity and usability are more successful than other techniques (Nitze et al. 2012). In both approaches used for classification, over-fitting is prevented by using cross validation in the evaluation of results. Furthermore, it is thought to prevent over-fitting by determining the coefficients in activation functions in ANN method and by determining the hyper parameters that adjust the margin range in SVM method (Kim 2003).

Root Mean Squared Error (RMSE), which is the evaluation criterion used in both prediction methods, is calculated by dividing the sum of the squares of the errors of a data set by the number of data and taking the square root of this value (Willmott et al. 2005). In the RMSE equation given in Equation 12, x is the actual value, x' is the predicted value, and n is the number of data.

$$OKHK = \sqrt{\frac{\sum_{i=1}^{n}(x-x')^2}{n}} \tag{12}$$

In the calculation given in Equation 12, since the squares of the errors are taken, the effect of the large errors in the dataset on the mean is also large, which allows to determine the effect of the large errors on the whole measurement (Chai et al. 2014). The RMSE value used as the evaluation criterion of the prediction problems is generally expected to be below 10% (Lee 2014).

Results

In this study, MLPNN and SVM machine learning methods were used for predicting the level of alexithymia (dependent variable) by using self-concept (SelfCncp), confusion and escape fantasies (ConfEs), personal maladjustment and desire for change (MalAdjus), loneliness/isolation (LoneIs) and hopelessness (Helples) features (independent variables) In addition, the correlation matrix and Fisher score analysis were applied to the data set for the extraction of the most effective features that constitute automatic thought fields in the prediction process. These results are shown in Table 1 and Table 2.

As shown in the Fisher Score analysis in Table 2, the features that affect the alexithymia level are directly proportional to the correlation matrix given in Table 1. As a result of the experimental studies performed, the fact that the independent variables with a score less than 0.75 were added to the classification decreased the success rate and 5 features (independent variables) were selected and the classification was performed. According to these two tables, it is seen that the most significant feature affecting alexithymia level is loneliness/isolation. Other effective features were self-concept, confusion and escape fantasies, hopelessness and personal maladjustment and desire for change, respectively.

Table 1. Correlation Matrix between the Features and Alexithymia Result

Variables	SelfCncp	ConfEs	MalAdjus	Lonels	Helples	Alexit	M	SD
SelfCncpt	1						19.04	8.39
ConfEsc	.82	1					14.07	6.24
MalAdjust	.76	.81	1				7.68	2.85
LoneIso	.77	.76	.82	1			9.22	3.87
Hopeless	.8	.8	.72	.74	1		7.83	3.98
Alexithymia	.59	.58	.52	.61	.56	1	50.23	10.7

SelfCncp: self-concept, ConfEs: confusion and escape fantasies, MalAdjust: maladjustment and desire for change, Alexit; alexithymia; Lonels: loneliness/isolation, Hopelessness: hopeless.

Table 2. Application of the Fisher Scoring Method for the feature selection in the data set

Variable	Fisher Score
LoneIso	0.92
SelfCncpt	0.87
ConfEsc	0.85
Hopelessness	0.81
MalAdjust	0.77

SelfCncp: self-concept, ConfEs: confusion and escape fantasies, MalAdjust: maladjustment and desire for change, Lonels: loneliness/isolation.

The hidden layer used in the MLPNN model consists of 10 neurons, and hyperbolic tangent function was used for activation in neurons and back-propagation algorithm was used for training. In the SVM model, comparisons were made using polynomial and Gauss kernel functions (Soman et al. 2011).

In this study, randomly selected 10-fold crossover validation method was applied, which allows unbiased testing of the MLPNN and SVM models, to the dataset prepared for the prediction of alexithymia. The data set we use to train machine learning models is called a training data set. The remaining part of the data set, which is allocated to perform an objective evaluation of the final model created as a result of the training, is called the test data set. The testing process provides the gold standard for the evaluation of the model. The data set is usually divided into 70% training and 30% testing (Kohavi 1995). In this method, the data set is separated into 2 parts, as training and test. In the study, the data divided into 70% (497) training and 30% (217) test data for the machine learning methods, as generally used in such studies (Hastie et al. 2009). Experimental analyzes were performed with 5 attributes from 714 subjects. When the literature is examined, it is considered that the sample size of 714 individuals used in the study is sufficient for the evaluation of the two machine learning methods (Öztemel 2003, Steinwart et al. 2008). In order to evaluate results objectively, experiments were carried out by subjecting the data set to 10 different training stages by changing the positions of the data by keeping the distribution ratios same. Analyzes were repeated 10 times and the average of 10 different results was taken to ensure that the results were not directly affected positively in the cross-validation method. In addition, in each analysis, the train and test dataset were randomly distributed for objective evaluation. Root Mean Squared Error (RMSE) values obtained from these experiments are presented in Table 3.

Table 3. RMSE values of the models used for Alexithymia

Model	RMSE
MLPNN	5.04
SVM (Polynomial)	4.01
SVM (Gaussian)	4.26

Table 3 shows that the most successful model among the 3 methods used for the prediction of the Alexithymia level is the SVM model with the polynomial kernel function by 4.01 RMSE. The RMSE value approaching to zero is indicative of the success of the model we proposed. The predicted results of the most successful model from the test data set and the alexithymia level results are shown in Figure 3.

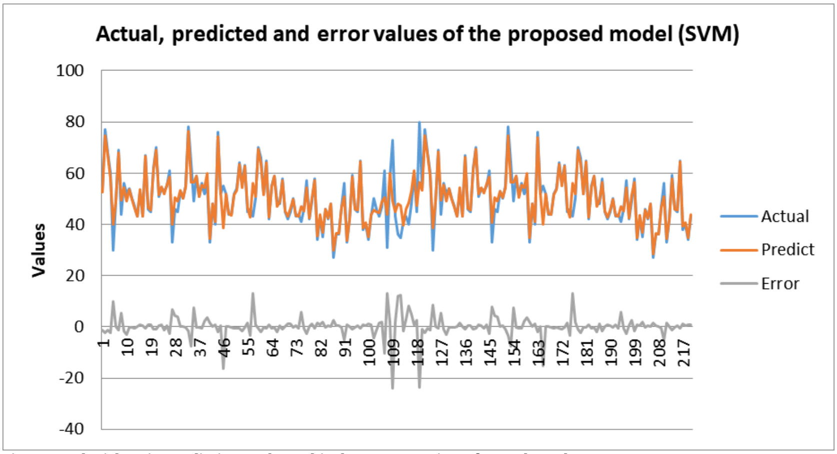

Figure 3. Alexithymia prediction and graphical representation of actual results

As shown in Figure 3, the actual values of the alexithymia prediction results obtained by applying the SVM method to the automatic thoughts scale, consisting of 5 features, yielded a prediction with 4.01 RMSE.

Regression Analyses

Before conducting the multiple regression analysis, the assumptions were examined. Within this scope, correlation coefficients were reexamined. The examination revealed that the correlation coefficient between LoneIso and MalAdjust; SelfCncpt and ConfEsc; MalAdjust and ConfEsc was .80 or higher in both analyses (Table 1). Moreover, variance inflation factor (VIF) of them was above 5. Thus, these variables were excluded from the dataset since this situation indicated multicollinearity problem (Kline 2016). So most relational variables (LoneIso and SelfCncpt) with alexithymia were used in multiple regression analysis. The predictive power of automatic thoughts on alexithymia can be seen in Table 4.

Table 4. Predictive power of automatic thoughts on alexithymia

	β	*t*	R^2	ΔR^2	*F*
			.65	.42	52.53**
LoneIso	.37	4.20**			
SelfCncpt	.21	2.22*			
Hopeless	.12	1.29			

*p<.05, ** p<.01, n=714; Lonels: loneliness/isolation, SelfCncp: self-concept, Hopelessness: hopeless.

As can be seen in Table 4, lonelso and selfCncpt predicted alexithymia significantly ($p < .01$). Automatic thoughts contribution to total variance was 42% (R2 =.42). Lonelso varible was the variable which contributed to the model most (β =.37, t=4.20, p<.01). These results are consistent with Fisher's score analysis results.

Discussion

As a result of the experimental studies on estimating the level of alexithymia using the dataset for automatic thoughts scale, the most successful prediction model was found to be the SVM model with the polynomial kernel function by 4.01% RMSE. In the SVM model used in the study, Polynomial and Gaussian kernel functions and in the MLPNN model are Step, Sigmoid, Hyperbolic Tangent and threshold value activation functions. As a result of analyzes performed, it is concluded that the data set has a polynomial distribution as the highest prediction success is in the SVM model with the polynomial kernel function. When the findings of the polynomial distribution are examined, it is seen that automatic thoughts can predict the level of alexithymia to a great extent. This finding suggests that considering the alexithymia in the context of cognitive behavioral therapies would be beneficial in terms of treatment. This finding is also supported by the related literature (Sifneos et al. 1977, Krystal 1982, Lesser 1985, Taylor et al. 1992). Krystal (1982) stresses that psychotherapeutic treatments concentrate on the origins of behavioral problems rather than on inadequacies such as emotional regulation and identification, which suggests that it will not be sufficient in the treatment of alexithymia. This insight has been supported by studies (Lesse 1985, Yu et al. 2013).

However, many researchers have argued that incomplete cognitive development of individuals' lies at the origin of alexithymia, and that individuals with alexithymia cannot differentiate their emotions and reveal their emotions with somatic symptoms (Lazarus 1982, Martin et al. 1986). This is interpreted as individuals with alexithymia use primitive cognitive schemas. In addition, it is possible to come across studies reporting that the intervention programs developed within the scope of cognitive behavioral therapy reduce the level of alexithymia (Taylor et al. 1992, Bach et al. 1995, Rosemblum et al. 2005, Spek et al. 2008, Rufer et al. 2010). As can be seen, the main premise of this research that suggests automatic thoughts predicts the levels of alexithymia is compatible with the literature. This finding of the research and the related literature indicate that cognitive-behavioral therapies have an important place in the treatment of alexithymia.

According to the Fisher Score method and regression analysis used in the study, the major automatic thought factor that predicts the level of alexithymia is loneliness and isolation. This is an expected result. Because, inability to express emotions negatively affects interpersonal relations and communication (Spitzer et al. 2005, Vanheule et al.

2007). For example, in the qualitative aspect of his research, Koçak (2016) has revealed the expressions of respondents on alexithymic emotions. And, he has noted that these expressions have been especially related to loneliness and isolation. Koçak also reported in the same study that the decrease in level of alexithymia also reduced the level of loneliness. Arcan and Yüce (2016) and Craparo (2011) have reported high levels of loneliness and alexithymia among individuals with Internet addiction, and have argued that individuals with a high alexithymia use the Internet as a kind of isolation tool. Besharat (2010), on the other hand, states that individuals with alexithymia cope with problems in an evasive manner. In other words, individuals with alexithymia prefer to isolate themselves. Ogrodniczuk, Sochting, Piper and Joyce (2012) have similarly stated that group-therapy improves inter-individual relationships by reducing the level of alexithymia.

Considering all these findings and literature together, it may be advisable to conduct studies within the scope of the cognitive behavioral therapy while working with individuals with alexithymia. In addition, since individuals with alexithymia experience problems on the basis of loneliness and isolation, it may be beneficial for them to take advantage of psychoeducation programs in relation to interpersonal relations as well as emotion expression skills. Mental health practitioners can focus on loneliness and isolation when working with alexithymia. In the literature, it has been stated that supportive and educational approaches should come to the fore in the treatment of alexithymia (Sifneos et al. 1977, Krystal 1982, Taylor et al. 1992, Rufer et al. 2010). Consequently psychoeducation programs can applicable for dealing with loneliness and isolation when working with alexithymic individuals. Cognitive behavioral therapy may be the basis of these studies.

In this study, alexithymia was examined on the basis of automatic thoughts, among the concepts of cognitive behavioral therapy. In the future studies, it may be advisable to investigate the relationship between the different concepts of cognitive therapy and the level of alexithymia. In addition, this research was conducted by a relational model. In future studies, research findings can be controlled using experimental and/or longitudinal designs. In this way, it will be possible to establish more healthy causal correlations among the variables.

Finally, it is seen that Fisher Score method for the feature selection and the ANN and SVM machine learning methods for the prediction can be used in relational screening studies. These methods are known to be powerful methods for the feature selection and prediction. Therefore, these methods should be used more widely in similar studies to be conducted in the future..

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Authors Contributions: All authors attest that each author has made an important scientific contribution to the study and has assisted with the drafting or revising of the manuscript.

Ethical Approval: Written informed consent was obtained from all participants.

Peer-review: Externally peer-reviewed.

Conflict of Interest: No conflict of interest was declared by the authors.

Financial Disclosure: The authors declared that this study has received no financial support.