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Prediction of pre-service teachers' academic self-efficacy through machine learning approaches

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ABSTRACT

The aim of this study was to investigate the extent to which pre-service teachers' belief in academic engagement, student burnout, and proactive strategies predicts academic self-efficacy through machine learning approach. The study group consisted of 446 pre-service teachers at Sivas Cumhuriyet University, Faculty of Education. The Academic Self-Efficacy Scale, Academic Involvement Scale, Maslach Burnout Inventory-Student Scale, and Proactive Strategy Scale were used for data collection. In data analysis, two different machine learning approaches were used; linear regression and artificial neural networks (ANNs). As a result of the regression analysis, a positive, and significant relationship was found between the academic self-efficacy of pre-service teachers, their academic engagement, and proactive strategy. Also, there was a negative and significant relationship between pre-service teachers' academic self-efficacy and academic burnout. Considering the results of the regression analysis, academic engagement, academic burnout, and proactive strategy together explained 38% of academic self-efficacy. When the ANNs results were examined, it was seen that these three variables explained 77% of academic self-efficacy. Therefore, it was understood that ANNs perform better than multiple regression in predicting academic self-efficacy.

Keywords: Academic self-efficacy, academic engagement, student burnout, proactive strategies, multiple regression, artificial neural networks.

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INTRODUCTION

The expeditious development in data analysis in the last years has made it important how to extract valuable information from huge volumes of data (Xu et al., 2021). Artificial intelligence (AI) applications that imitate human characteristics such as learning, perception, problem-solving, and reasoning have been rapidly applied in many areas in recent years (Abdallah et al., 2020). Artificial neural networks (ANNs), an important AI technique, have attracted great attention due to their features such as processing big data, mapping relationships, and predicting outcomes (Wang et al., 2018). ANNs use probabilities of all interactions between predictor variables to better predict the outcome variable (Cascallar et al., 2015) and offer us the opportunity to obtain a prediction even when there is a nonlinear relationship between independent, and dependent variables (Somers and Casal, 2009). ANNs also enable "the analysis of vast volumes of information, and the construction of predictive models regardless of the statistical distribution of the data" (Garson, 2014). However, since more familiar analyses such as multiple linear regression are used in educational research, the use of ANNs has not yet become widespread (Bonsaksen, 2016).

Theoretical framework

Academic self-efficacy

Self-efficacy means to one's views about the ability to deal with certain academic tasks (Owen and Froman, 1988; Sharma and Nasa, 2014). This definition has two important aspects. First, self-efficacy is one's belief in his ability and therefore may differ from one's actual ability in a particular subject. The second important aspect is the idea that individuals use these judgments while trying to reach some goals (Artino Jr, 2012).

According to Bandura (1977), personal efficacy expectations are based on four sources: Performance achievements, vicarious experience, verbal persuasion, and emotional arousal. Performance achievements are specifically based on personal experience. Achievements raise mastery expectations; repeated failures bring them down, especially at the beginning of the performance. People are not affected by their experience as the only source of information about their level of self-efficacy. Many expectations are derived from indirect experiences. By observing the performance of others, the individual believes that if others can do it, he or she can do it. Bandura (1977) called this vicarious experience. Indirect experience is less reliable information about one's abilities as it is based on inferences from social comparison. Verbal persuasion is based on suggestions. People may believe that, through suggestions, they can successfully deal with things that have circumvented them in the past. Since the efficacy expectations promoted in this way are not empirically grounded, they are weaker than self-efficacy perceptions from one's achievements. Emotional arousal is another resource that can affect perceived self-efficacy in dealing with problems encountered. Because high arousal often leads to failure, people do better when there are no aversive stimuli around.

People with a strong sense of competence overcome difficult tasks, set challenging goals for themselves, and do not give up on these goals. When faced with failure, they refocus on the task. On the contrary, people with low proficiency levels avoid difficult tasks, are easily affected by all kinds of negative situations when faced with difficult tasks, and give up quickly. When faced with failure, they lose faith in their abilities (Bandura, 1994; Schunk, 1991). Students with a high sense of self-efficacy use more cognitive strategies that enable them to learn effectively, and use their time and learning environments more consciously in organizing and evaluating their work (Chemers et al., 2001). Therefore, it is understood that one of the most important factors affecting the success of students in academic life is self-efficacy (Hayat et al., 2020).

General self-efficacy is broadly divided into two categories: academic self-efficacy and cognitive ability (Musa, 2020). Academic self-efficacy is defined as students' belief in their ability to complete a given academic task (Chemers et al., 2001; Khan, 2013; Solberg et al., 1993; Tsai and Tsai, 2010), shown to be a considerable factor in academic achievement (Khan, 2013), student success (Elias and Loomis, 2002), and engagement in schools (Sharma and Nasa, 2014). Academic expectation beliefs have two dimensions. Academic outcome expectations are one's belief about what results of certain behavior will lead to, and academic efficacy expectations are a student's opinions about his capacity to demonstrate the required behaviors to achieve a certain goal (Sharma and Nasa, 2014).

Academic engagement

Engagement refers to the level of a person's behavioral, and emotional involvement in a task or activity (Reeve et al., 2004). Finn and Voelkl (1993) expressed involvement as "the youngster's attending school, and class, paying attention to the teacher, and taking part in curricular activities by responding appropriately to directions, questions, and assignments".

Astin (1999) defined academic engagement as the physical and spiritual energy that the student expends in school life. And he described a highly engaged student as someone who spends a much time on campus, communicates frequently with academics and faculty staff, and their friends on campus, and attends student organizations. In contrast, he defined an uninvolved student as an individual who spends little time on campus, does not establish frequent relationships with others, and does not participate in extra-curricular activities.

Astin (1999) was influenced by the research on the effect of student involvement on dropping out and researched to examine the participation phenomenon more deeply. As a result of his study, he identified several forms of student involvement: “place of residence, honors programs, undergraduate research participation, social fraternities, and sororities, academic involvement, student-faculty interaction, athletic involvement, and involvement in student government”. He defined academic engagement as the complex of time students spend studying, how hard they study their studies, their degree of interest in work areas, and good work habits.

Studies on academic involvement (Appleton et al., 2008; Fredricks et al., 2004; Linnenbrink and Pintrich, 2003; Sakurai and Pyhältö, 2018) divided academic involvement into three categories: behavioral, cognitive, and affective-emotional. *Behavioral engagement* is about school related-activities such as classroom learning and academic (Fredricks et al., 2004). Linnenbrink and Pintrich (2003) described behavioral involvement as students' hard work on a given task, persistence when faced with difficulties, and asking for help from peers or teachers. Behavioral engagement consists of students' participation in various educational activities by interacting with friends and academics (Sakurai and Pyhältö, 2018). *Cognitive involvement*, which refers to taking responsibility for learning, includes being “willing to exert the effort necessary for the comprehension of cognitively complex ideas, and the acquisition of difficult skills" (Fredricks, 2011, p. 328). The fact that students are physically active, and participate in learning activities does not always guarantee that real learning has occurred. Even if some students are listening to the teacher, they may not be mentally thinking about the material being taught. Or, learning may not occur even if some students make the behavioral, and cognitive effort. For this reason, Linnenbrink and Pintrich (2003) stated that real cognitive involvement can provide a window into the nature of students' questions, students' replies to teacher questions, and students' sharings to discussions in class. *Emotional involvement* refers to the good, and bad feelings of the student towards school, teacher, and activities. While students may experience good feelings such as happiness, enthusiasm, and interest in the educational environment, they may also develop bad emotions such as boredom, and anxiety (Fredricks, 2011).

Astin (1984, p. 298) stated that "the quality, and quantity of student involvement" directly affects the level of learning and development of the student. Students who are highly engaged in academic activities have good academic marks (Heikkilä and Lonka, 2006). High academic involvement ensures a high internalized sense of identification (Finn and Voelkl, 1993). In addition, low academic involvement can have negative effects such as disruptive behavior in the classroom, truancy, absenteeism, dropping out of school, and juvenile delinquency (Finn, 1989).

Various researches have explained that higher involvement is related to higher academic success (Astin, 1993; Henrie et al., 2015; Ogbu, 2003; Smerdon, 1999), an increase in factual knowledge, and a range of general cognitive and intellectual skills (Pascarella and Terenzini, 2005), a reduced likelihood of dropout (Henrie et al., 2015; Ogbu, 2003; Smerdon, 1999).

The more a student is involved in the learning process, the more he learns and the better his performance, the higher his self-efficacy will be (Linnenbrink and Pintrich, 2003). Individuals with strong efficacy beliefs are more likely to be persistent while performing a task, and to work without giving up when faced with difficulties. Rather, individuals with a weak perception of efficacy may not complete their studies successfully by giving up easily when faced with difficulties, even if they have the knowledge, and skills to perform the task (Linnenbrink and Pintrich, 2003).

Burnout

College students may experience stress about the deficiency of quality time they spend with their families, and peers, their future career expectations, and the effectiveness of their work (Campos et al., 2011), and this stress can create a sense of burnout over time. Burnout syndrome has been defined as the reaction to the stress encountered in the profession in certain occupational groups (Morales-Rodríguez et al., 2019). Various authors agree in pointing to Herbert Freudenberger, as the first to speak of burnout, ("being burned out", "consumed", "off"), and to Cristina Maslach, as the one who established a line of research on burnout (Caballero et al., 2010). Burnout is a psychological syndrome that occurs in the areas of emotional exhaustion, depersonalization, and a decrease in personal achievement in persons who work by interacting with others (Maslach et al., 1996). Emotional exhaustion that makes the individual feel psychologically intolerant is an important sight of burnout syndrome and refers to the individual's negative, cynical attitude toward others. Another sight of burnout syndrome is depersonalization. The development of depersonalization seems to be associated with emotional exhaustion. The third sight of burnout syndrome, the decrease in personal achievement, means the disposition of the person to evaluate himself negatively about his work (Maslach et al., 1996).

Like those working in any profession, students work long hours, prepare assignments, and have to submit these assignments on a certain date. Therefore, university students are exposed to burnout, and its negative effects (Law, 2007). In addition, students can experience work stress due to overcrowded classrooms, exams, subtasks, extracurricular activities, excessive academic demand, perceived workload, time, and resource constraints (Pala, 2012). Academic burnout is the attitude that negatively affects the educational process, and is affected by anxiety, which reduces the energy and attention required for cognitive tasks (Pamungkas and Nurlaili, 2021). Academic burnout, like occupational burnout, can be divided into three dimensions: exhaustion, cynicism, and academic inefficacy (Schaufeli et al., 2002).

While some students are sufficient and successful in their academic studies, some students cannot produce a solution when they encounter a problem in their academic studies or think that they will not succeed and begin to show avoidance behaviors (Caballero et al., 2010). Students who experience burnout lose their motivation, which causes them not to attend classes, and not to do their homework, and also negatively affects their academic success (Sugara et al., 2020). To cope with this, students can use reactive or proactive strategies.

Proactive strategies

People often recognize the clues that suggest a problem, and take steps to deal with it before it arises. Proactive behaviour can be defined as people anticipating potential problems and stressors and taking action to prevent them (Aspinwall and Taylor, 1997). Proactive coping differs from traditional coping approaches in terms of features such as being future-oriented rather than compensating for past losses, and losses, having goal management and having more positive motivation (Greenglass and Fiksenbaum, 2009).

Aspinwall and Taylor (1997) defined the proactive coping process as five stages: The first stage of proactive coping is the creation of resources, and skills before any stressor (*resource accumulation*). At this stage, stressors are identified, and the person is prepared to manage the chronic burden as much as possible. The second stage is *attention recognition*. Recognition refers to the ability to foresee the problem situation. In the third stage, *initial appraisal*, evaluations are made about the current state of the problem situation. The fourth stage is *preliminary coping*. Successful proactive coping includes both cognitive and behavioral activities such as planning or taking action. The final stage in the proactive coping process is *eliciting and using feedback.* It refers to the use of feedback on the development of the stressful problem situation, the effects of the person's interventions on the stressful event, and whether additional coping efforts are required.

In recent years, interest in the role of students' beliefs in the learning process has increased in studies conducted in educational settings, and the concept of student self-efficacy, one of these issues, has attracted the attention of many researchers. In these researches, academic self-efficacy has also been found to be an important predictor of academic performance and achievement (Basith et al., 2020; Elias and Loomis, 2002; Ferla et al., 2009; Kırmızı, 2015; Verešová and Foglová, 2017). Academic self-efficacy has also been related to some non-academic variables, one of which is prosocial behavior (Bandura et al., 1996), academic self-esteem (Ahmadi, 2020), academic motivation (Akomolafe et al., 2013; Malkoç and Kesen Mutlu, 2018), academic procrastination (Malkoç and Kesen Mutlu, 2018), academic self-concept (Akomolafe et al., 2013; Ferla et al., 2009), participation in the study, academic burnout (Akter, 2021; Charkhabi et al., 2013; Jenaabadi et al., 2017; Naderi et al., 2018; Özhan, 2021; Rahmati, 2015; Sabharwal et al., 2021), the quality of learning experience (Charkhabi et al., 2013). This study has tried to contribute to the literature by trying to determine the relationship between the concept of academic self-efficacy and academic participation, burnout, and proactive strategy.

Aim of the study

The main purpose of this study is to investigate the relationship between pre-service teachers' academic engagement, student burnout, proactive strategies, and their academic self-efficacy through different machine-learning approaches (multiple linear regression and ANNs). In addition, the sub-problem of the research is to what extent these variables predict academic self-efficacy.

METHODOLOGY

Sampling

The research group consisted of 446 pre-service teachers attending Sivas Cumhuriyet University Faculty of Education, Department of Mathematics Teaching (46 students, 10.3%), Guidance, and Psychological Counseling (79 students, 17.7%), Science Education (24 students, 5.4%), Social Studies Teaching (55 students, 12.3%), Classroom Teaching (87 students, 19.5%), Preschool Education (39 students, 8.7%), Turkish Language Teaching (80 students, 17.9%), and English Language Teaching (36 students, 8.1%) in the 2020–2021 academic year. 322 (72.2%) were female, and 124 (27.8%) male. 102 (22.9%) of the students were seniors, 118 (26.5%) were in the second grade, 130 (29.1%) were in the third grade, and 96 (21.5%) were in the fourth grade.

Instruments

The Academic Self-Efficacy Scale, Academic Involvement Scale, Maslach Burnout Inventory–Student Scale (MBI-SS), and The Proactive Strategy Scale were used for data collection.

Academic self-efficacy scale

The Academic Self-Efficacy Scale prepared by Owen and Froman (1988) was adapted into Turkish by Ekici (2012). The authors conducted a validity and reliability study of the scale on 683 university students. The scale consists of three sub-dimensions, namely social status, cognitive practices, and technical skills, and 33 items. The results of the validity and reliability studies carried out by the researchers showed that the scale can be used in Turkish conditions.

The construct validity and reliability calculations of the scale were made again with the data of this research. CFA results from this research were: ($\chi 2/df$ = 3.45; RMSEA = 0.082; CFI = 0.80; GFI = 0.78; AGFI = 0.75; NFI = 0.78; SRMR = 0.082; RMR = 0.088). The Cronbach Alpha reliability coefficient for the overall scale was found to be 0.82. These results show that the validity and reliability values of the scale are high.

Academic involvement scale

The scale originally developed by Huang (2007) was adapted into Turkish by Buluş (2015). For the reliability and validity study, the researcher applied the scale to 336 undergraduate students. Results showed that the factor structure of the Turkish version of the AIS was consistent with the original, and therefore suitable for use by Turkish candidates.

The construct validity and reliability calculations of the scale were made again with the data of this research. CFA results from this research were: ($\chi 2$/df = 2.60; RMSEA = 0.060; CFI = 0.98; GFI = 0.99; AGFI = 0.97; NFI = 0.96; SRMR = 0.033; RMR = 0.025). The Cronbach alpha reliability coefficient for the overall scale was found to be 0.72. These results show that the validity and reliability values of the scale are high.

Maslach burnout inventory–student scale (MBI-SS)

The MBI-SS, developed by Schaufeli et al. (2002), was adapted into Turkish by Çapri et al. (2011). The authors conducted a validity and reliability study of the scale on 782 university students. As a result of confirmatory factor analysis (CFA), a three-factor structure consisting of 13 items was obtained ($\chi 2$/df = 2.87-5.94; RMSEA, .049-.080; TLI = .97-.93; CFI = .98-.95; GFI = .97-.93; AGFI = .95-.90; SRMR=.037-.048). Item-total test correlations were calculated, and correlation values of sub-factors were found to vary between .32, and .69. While the Cronbach Alpha internal consistency coefficients calculated to determine the reliability of the scale were found as .76, .82, and .61, respectively, and the test-retest reliability results were found as .76, .74, and .73. As a result, it was understood that the scale had a sufficient level of the item-total test correlation coefficient, internal consistency, correlation coefficient with similar scales, score stability, and construct validity obtained as a result of the test-retest reliability coefficient.

The construct validity and reliability calculations of the scale were made again with the data of this research. CFA results from this research were: ($\chi 2$/df = 3.61; RMSEA = 0.077; CFI = 0.96; GFI = 0.93; AGFI = 0.89; NFI = 0.95; SRMR = 0.056; RMR = 0.090). The Cronbach Alpha reliability coefficient for the overall scale was found to be 0.84. These results show that the validity and reliability values of the scale are high.

Proactive strategy scale

The Proactive Strategy Scale was developed by Pietarinen et al. (2013). The scale consists of 7 items and two sub-dimensions (self-regulation and co-regulation). Items are scored on a 7-point Likert-type scale ranging from totally disagree (1) to totally agree (7).

The scale was adapted to Turkish by the researcher. The researcher translated the scale into Turkish and then, two linguists checked it. After, it was evaluated by experts in terms of conformity to Turkish, content, assessment, and evaluation. The scale, which made some minor adjustments in line with the opinions received, was applied to 230 university students to construct validity, and reliability studies. CFA was performed to verify the constructed structure. The results of the CFA showed that the scale is one-dimensional like its original version. The scale consists of 7 items. The CFA results for the models were: ($\chi 2$/df = 3.65; RMSEA = 0.078; CFI = 0.98; GFI = 0.97; AGFI = 0.94; NFI = 0.97; SRMR = 0.044; RMR: 0.081). These fit indexes showed that the model provided a good fit to the data. The Cronbach Alpha reliability coefficient for the overall scale was found to be 0.81. The results obtained showed that the scale can be used in Turkish conditions.

Data analyses

The data obtained from the scales were analyzed using SPSS version 26 when doing regression analysis. First, correlation analysis was performed to determine the relationship between the variables. Then, a multiple regression analysis was performed. To perform multiple linear regression analysis, first of all, the necessary assumptions for the regression analysis were checked and met. As seen in the Pearson correlation analysis in Table 1, normality, and linearity were met, and there was no homoscedasticity. Since the Mahalanobis distance of 6 data exceeded the limit (greater than 16.27), these data were determined as outliers and were excluded from the data set. Multiple regression analysis was performed with 440 data. Multicollinearity was checked by variance inflation factor values (lower than 10), tolerance (lower than 1), and condition index (lower than 24). These indicate no strong correlation between academic self-efficacy, academic engagement, student burnout, and proactive strategies. Finally, the Durbin-Watson statistic was 1.12, indicating no residual error.

The computer-aided software program MATLAB R2013 (demo) was used for the ANNs calculations.

Artificial neural network (ANNs) modeling

ANNs were used to model the relationship between the variables in the study, and accordingly the estimation of the dependent variable (academic self-efficacy). A simple ANNs architecture is presented in Figure 1. Accordingly, inputs are x1, x2,… xn, and the weight coefficients of each input are Wk1, Wk2,… Wkn. “Here, xn represents the input signals, and Wkn represents the weight coefficients

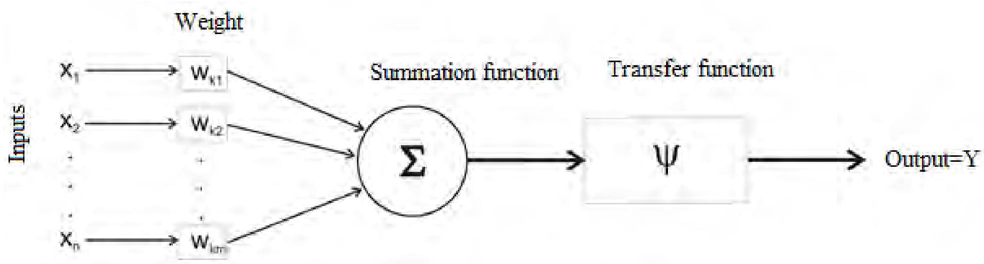

Figure 1. ANNs cell model.

of these signals. The core gives the weighted sum of all input signals. The results obtained from the thresholding function of the network are shown with Y" (Yildiz, 2017).

Neuron layers are classified as input, hidden, and output. The input system, which receives external information such as sensory receptors, is formed from neurons in the input layer. To transmit information, neurons in the hidden layer simulate a biological neural network. The neurons in the output layer determine the decision output (Xu et al., 2021).

According to Adamovic et al. (2017), "independent input parameters are generally selected for ANNs modeling to establish their nonlinear relationship with output parameters. However, the potential correlations among the input parameters can significantly affect the modeling performance". In this study, academic engagement, academic burnout, and prosocial behavior were determined as inputs and academic self-efficacy as output. The simple architecture of the back propagation algorithm of the ANNs is given in Figure 2.

In ANNs model establishment, it is necessary to optimize the number of hidden layer nodes. In the reviewed studies, hidden layer nodes were assigned at different ranges (Xu et al., 2021). Models 3-3-1-1, 3-4-1-1, and 3-5-1-1 were established in this study. The most suitable model was selected by statistical analysis for each model. The ANNs structure used in the study is given in Figure 3.

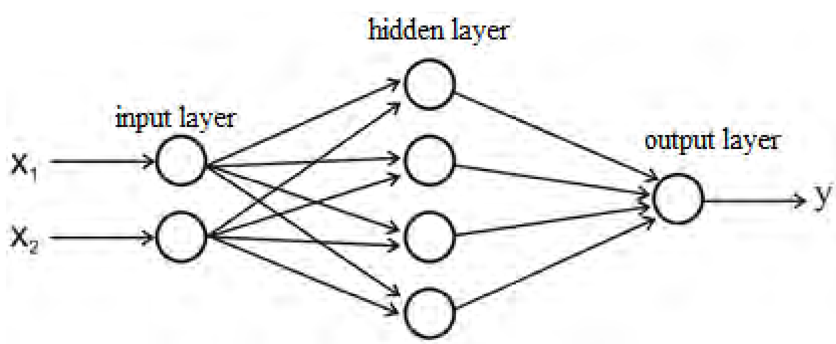

Figure 2. Simple architecture of ANNs.

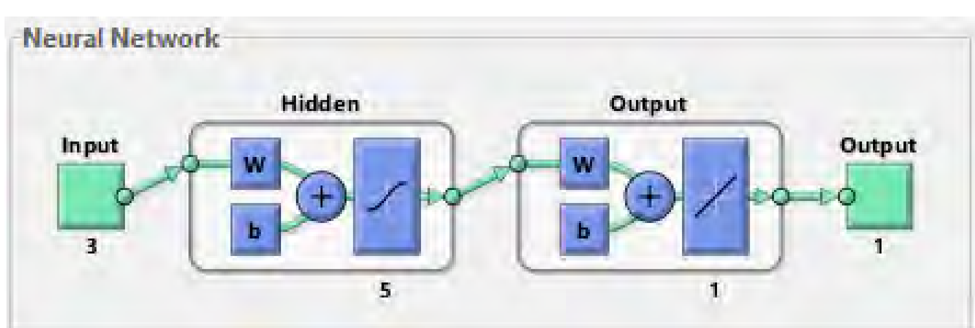

Figure 3. ANNs structure.

Optimization of input parameters is important in modeling ANNs. Removing some of the interrelated input parameters does not have a negative effect on the performance of ANNs (Walczak and Cerpa, 1999). It can even improve the performance of ANNs (Antanasijevic et al., 2013).

FINDINGS

Preliminary analysis of the relationship between academic self-efficacy, academic engagement, student burnout, and proactive strategies

Participants obtained a mean level of academic self-efficacy located at 100.62 (SD = 17.118); as for academic engagement, the mean score was 12.36 (SD = 2.800); in the case of student burnout, the mean score was 38.69 (SD = 9.405), and for proactive strategies, the mean score was 36.11 (SD = 6.434).

Table 1 shows the relationship between academic self-efficacy, academic engagement, student burnout, and proactive strategies. It is seen that there is a significant, and linear relationship between academic self-efficacy, academic engagement, and proactive strategies, and there is a significant, and inverse relationship between academic self-efficacy and student burnout.

Multiple linear regression analysis results

The regression analysis result of predicting academic self-efficacy which is related to academic engagement, student burnout, and proactive strategies is given in Table 2.

Table 1. Pearson correlations between the variables.

		Academic self-efficacy	Academic engagement	Student burnout	Proactive strategies
Academic self-efficacy	Pearson correlation	1.000	.543	-.422	.352
	Sig. (1-tailed)		.000	.000	.000
Academic engagement	Pearson correlation	.543	1.000	-.401	.253
	Sig. (1-tailed)	.000		.000	.000
Student burnout	Pearson correlation	-.422	-.401	1.000	-.305
	Sig. (1-tailed)	.000	.000		.000
Proactive strategies	Pearson correlation	.352	.253	-.305	1.000
	Sig. (1-tailed)	.000	.000	.000	

Table 2. Multiple regression analysis of variables predicting academic self-efficacy.

Variable	B	Std. Error	β	T	p	Bilateral r	Partial r
Constant	65.243	6.517	-	10.011	.000	-	-
Academic engagement	2.546	.255	.417	9.975	.000	.431	.377
Student burnout	-.362	.077	-.199	-4.684	.000	-.219	-.177
Proactive strategies	.496	.107	.186	4.637	.000	.217	.175
R = 0.613 F(3-436) = 87.552		R^2 = 0.376, *p < .01					

As a result of multiple regression analyses, it was determined that there was a significant relationship between academic engagement, student burnout, proactive strategies, and academic self-efficacy (R = .613; R^2 = 0.376; F(3-436) = 87.552; p < 0.01).

These variables together explain 38% of the variance in academic self-efficacy. According to the standardized coefficients (β), the order of importance of the predictor variables on academic self-efficacy is academic engagement (β = 0.417), student burnout (β = -0.199), and proactive strategies (β = 0.186). Considering the significance tests of the regression coefficients it is seen that all of the predictive variables (academic engagement, student burnout, and proactive strategies) are significant predictors of academic self-efficacy ($p < .01$).

The regression equation that predicts academic self-efficacy is as follows:

Ŷacademic self-efficacy= 65.243 + (2.546)Xacademic engagement - (0.362)Xstudent burnout + (0.496)Xproactive strategies.

Results of ANNs

The training, validation, and test data of the ANNs model, which gave the best prediction in the study, are given in Figure 4. The statistical performance of the models was evaluated using the Mean (μ). Standard Deviation (σ), and R^2 parameters. In addition. RMSE and MAPE values were calculated to evaluate the fit of the models developed between ANNs' estimated data, and the real data. RMSE is a measure of goodness of fit. It most appropriately defines a mean error measure to estimate the dependent variable (Singh et al., 2009). The statistical performance of the study is given in Table 3. Conjoint neural network studies usually use RMSE, MAPE, and R^2 criteria to evaluate the performance of a network by comparing error, and measured data. (Alves et al., 2018). RMSE and MAPE are calculated according to Equations 1 and 2:

$$RMSE = \sqrt{\frac{1}{n}\sum_{n}^{1}(t_i - z_i)^2} \quad (1)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|(t_i - z_i)|^2}{z_i} \times 100 \quad (2)$$

Where "t_i", and "z_i" are the estimated, and actual output, and "n" is the number of points in the data set.

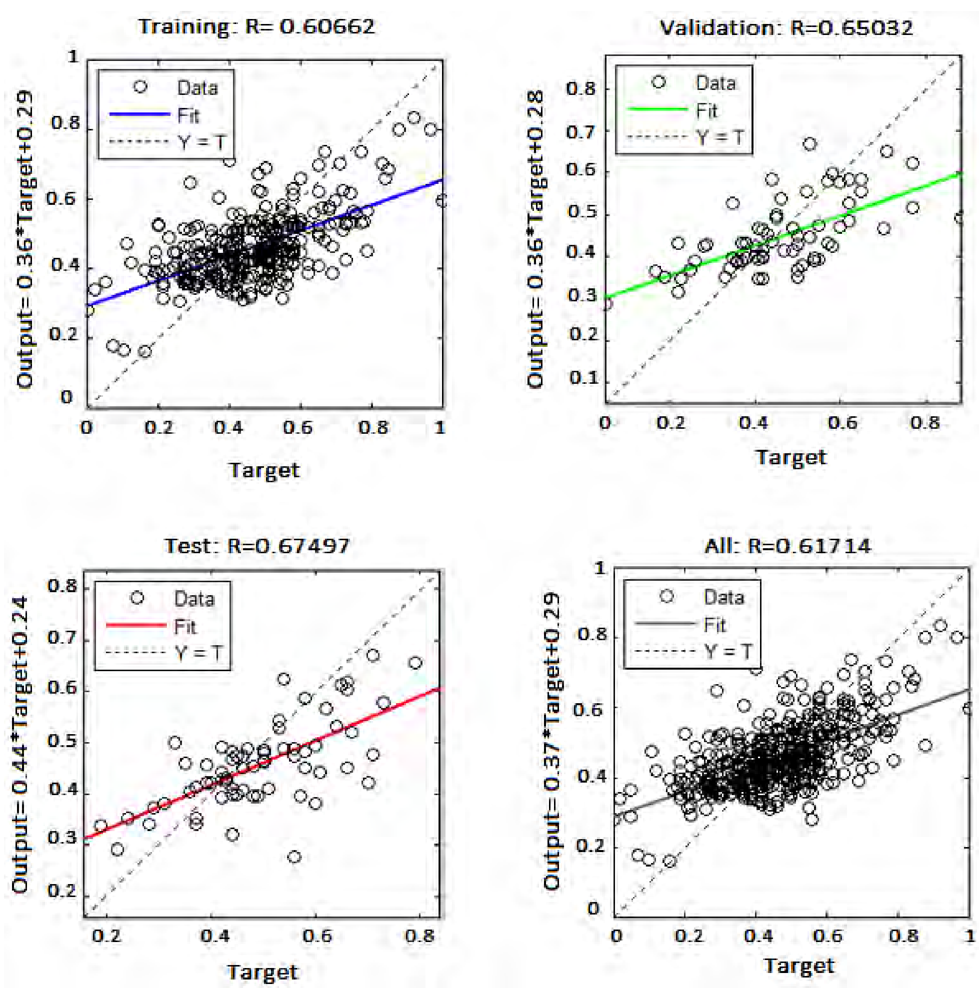

Figure 4. The training, validation, and testing data.

Table 3. Statistical performance of the ANNs models.

Model	Structure	R2	σ	μ	RMSE	MAPE
I	3-3-1-1	0.65	0.194	1.020	0.0071	16.22
II	3-4-1-1	0.60	0.266	1.071	0.0083	19.03
III	3-5-1-1	0.77	0.121	1.003	0.0071	9.52

As seen in Figure 4, ANNs proved to be an effective estimation method for academic self-efficacy with high R^2 values [R^2 = training (0.60). testing (0.67). validation (0.65)].

There is a significant relationship between the values obtained in the different models created (Table 3). However, the 3-5-1-1 model has the highest R^2 value (R^2=0.77), and this model was chosen as the most suitable model. RMSE value was calculated as 0.0071 for the I and III models and 0.0083 for the II model. The MAPE value is used to measure the predictive ability of a model. A lower MAPE value indicates the best model performance (Olyaie et al., 2015). The lowest MAPE was obtained in the 3-5-1-1 model selected in the study. In order to evaluate the success of ANNs modeling. which is used as an effective tool. the relationship between the prediction results provided by the ANNs model and the obtained data was compared. The results are given in Figure 5.

There is a good consistency between the estimated results of the ANNs model, and the calculated data (R^2 0.77) (Figure 5). The efficiency of the ANNs model was determined based on maximizing R^2 and lowering the Mean Squares Error (MSE) value of the test set (1–13 neurons correspond to the hidden layer). According to MSE, there was no significant change in the number of epochs for optimal ANN models after 7 stages (Figure 6).

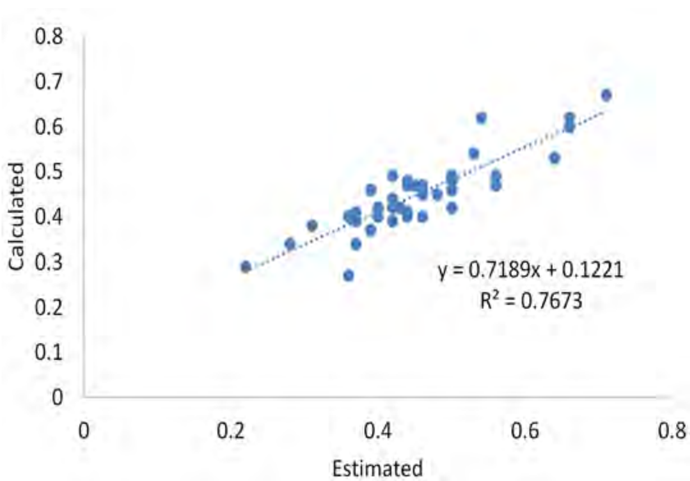

Figure 5. Calculated, and estimated academic self-efficacy.

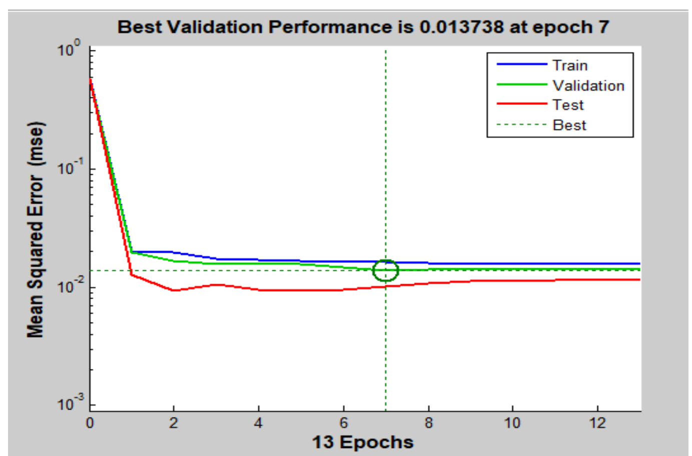

Figure 6. Number of epochs for optimal ANNs models according to MSE.

DISCUSSION

As a result of the regression analysis, a positive, moderate and significant relationship was found between the academic self-efficacy perceptions of pre-service teachers and their academic engagement (r = .543, p < .01). Consistent with this finding, previous researches have found a positive and significant relationship between academic self-efficacy and student engagement (Anggraini et al., 2014; Azila-Gbettor et al., 2021; Blas-Atencia et al., 2018; Helsa and Lidiawati, 2021; Hong et al., 2021; Momeni and Radmehi, 2018; Mozammel et al., 2018; Noreen vd., 2018; Olivier et al., 2019; Ozkal, 2019; Papa, 2015; Siu et al., 2014; Sotoodeh, 2017). Academic self-efficacy is a more detailed aspect of self-efficacy that reflects a student's views on their own proficiency in academic subjects (Noreen et al., 2018). Individuals with high self-efficacy are more willing to put in additional energy and effort to complete a task or assignment and thus become more engaged in studying with a high level of assimilation (Siu et al., 2014). On the contrary, as the individual's sense of self-efficacy decreases, the desire to participate in academic tasks and the effort and time spent on a task or assignment also decrease. Previous researchers have suggested that students with a low level of academic self-efficacy show more indifference in class (Bassi et al., 2007). According to the Expectancy Value theory, self-efficacy leads to both emotional and behavioral engagement. Engagement forms such as interest, effort, attention, and harmony are the elements that increase the student's desire to learn and proficiency in class assignments (Olivier et al., 2019). Student engagement seems to be related to academic self-efficacy as it reflects the ability of students to engage in their classes, such as attending, taking notes, doing homework, having the desire to learn, participating in class, asking questions and getting good grades, and being successful (Papa, 2015).

The findings showed that there was a positive, significant, and low correlation between pre-service teachers' perceptions of academic self-efficacy and proactive strategy ($r = .352$, $p < .01$). Consistent with this result, self-efficacy has a strong impact on proactive behavior in the study by Avsec and Jerman (2020). Burton and Nelson (2010) found a positive relationship between general self-efficacy and proactive coping strategies. Verešová and Malá (2012) found in their study that there is a significant positive relationship between proactive coping and self-efficacy. Proactive learners use all available resources, such as setting arduous goals and seeking new information, and new methods to achieve their goals. Individuals with high self-efficacy are superior in proactive goal formation (Lin et al., 2014).

The results also showed that there was a negative, significant and moderate relationship between pre-service teachers' perceptions of academic self-efficacy and academic burnout ($r = -.422$, $p < .01$). Other studies in the literature support this finding (Adams et al., 2020; Arlinkasari and Akmal, 2017; Bulfone et al., 2020; Fariborz et al., 2019; Jenaabadi et al., 2017; Khansa and Djamhoer, 2020; Kong et al., 2021; Korani, 2021; Kordzanganeh et al., 2021; Orpina and Praha, 2019; Özhan, 2021; Permatasari et al., 2021; Rahmati, 2015; Rohmani and Andriani, 2021). This result shows that as academic self-efficacy increases, academic burnout decreases and vice versa. A high self-efficacy belief increases one's motivation and emotional well-being in the face of difficulties, and also makes the person less exposed to stress, burnout, and depression (Kaiser, 2011). Individuals with low academic self-efficacy are prone to stress and depression because their problem-solving skills are low. Excessive and constant stress causes individuals to experience academic burnout (Rahmati, 2015 cited in Khansa and Djamhoer, 2020).

Another finding of the study is related to the power of the independent variables to explain the dependent variable. According to the results of the regression analysis, academic engagement, academic burnout, and proactive strategy together explain 38% of academic self-efficacy. When the ANNs results were examined, it was seen that these three variables explained 77% of academic self-efficacy. Therefore, it is understood that ANNs perform better than multiple regression in predicting academic self-efficacy. It is understood that ANNs give higher results than traditional statistical methods in studies conducted with student variables in the literature. In many studies conducted to predict student achievement, it is reported that ANNs work better than classical statistical methods. Turhan et al. (2013) used ANNs to predict the performance of university students and according to the results, ANNs showed higher estimation success than regression analysis on the same data set. Similarly, in the study conducted by Bahadır (2015), ANNs' results to predict student achievement were higher than logistic regression. It has been stated that artificial neural networks can be preferred in cases where the multiple regression analysis estimations and assumptions are not met and the analysis cannot be performed. Apart from this, it has been proven in studies (Ahangar et al., 2010; Alqahtani and Whyte, 2016; Çalışkan and Sevim, 2019; Ilaboya and Igbinedion, 2019) conducted in different fields that ANNs models have a better fit and prediction than regression models. In these studies, it was revealed that ANNs have a larger estimation and fewer erroneous results compared to multiple regression analyses.

Conclusion

In this study, it was tried to determine to what extent pre-service teachers' academic engagement, student burnout and proactive coping strategies predict academic self-efficacy with machine learning approach. Two different machine learning approaches, linear regression and artificial neural networks (ANNs) were used in data analysis. As a result of regression analysis, a positive and significant relationship was found between pre-service teachers' academic self-efficacy, academic engagement and proactive coping strategies. In addition, a negative and significant relationship was found between pre-service teachers' academic self-efficacy and academic burnout. According to the results of the regression analysis, academic engagement, academic burnout and proactive strategy together explain 38% of academic self-efficacy. According to the ANNs, these three variables explained 77% of academic self-efficacy. This proves that ANNs perform better than multiple regression in predicting academic self-efficacy.

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