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Impact of satisfaction, personality and learning style on educational outcomes in a blended learning environment

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ABSTRACT

Several factors influencing the educational outcomes in a blended learning environment have been explored in an attempt to predict student's academic performance and transferable skills. This research explores personality traits, learning style, satisfaction and their correlation to educational outcomes in a blended learning scenario that involved game-based learning strategies, flip teaching techniques and video conferencing sessions. At the end of the semester teachers evaluated the grades and skills of 142 K12 students that participated in the study in order to construct a prediction model and analyze the impact of the personality, learning style and satisfaction on educational outcomes. We constructed two ANFIS models to predict the grades and skills in the given learning setup, and two linear regression models to compare the results with ANFIS models. The ANFIS models explaining about 94% and 92% of variances in grades and skills outperformed the linear regression models explaining 81% and 69% of variances.

1. Introduction

The student-centered educational approaches emerged as alternative to the traditional teacher-centered education, by bringing the student's engagement with the educational activities in the center of the learning process with respect to their individual abilities and interests. The objective is to deliver motivated learner that is focused, self-determined, persistent and enthusiastic about the educational activity he is engaged in. Personalizing education for students produces multiple benefits regarding the academic performance, as well as behavioral gains such as student retention in the education, responsibility, and development of transferable skills like collaboration, communication, and problem solving. Besides tending to achieve multiple educational outcomes, this approach broadens the role of teachers as educators, facilitators, motivators, etc. The gradual shift from the traditional instruction models towards student-centered ones promotes understanding above pure memorization of the educational content, knowledge retention and positive relationship with the teacher during the carefully created synchronous and asynchronous learning events (Kain, 2003).

Blended learning is a formal student-centered educational approach that combines the best practices of traditional education and modern online approaches. The online learning sessions and traditional classroom setup are connected within a course as complementary modalities providing integrated learning experience for each student. This approach promotes the use of technology as a discovery-based tool in education, having in mind the learning needs of modern students. The students are encouraged to take an active role in the educational process through carefully planned activities such as collaborative work on certain tasks, participation in the evaluation process, self-directed guides, and synchronous and asynchronous delivery of learning material (Osguthorpe & Graham, 2003).

Providing a diverse blended educational environment adaptive to individual preferences of the student, would enable learners to achieve optimal learning performance. Personality traits, learning approaches, intellectual ability and satisfaction are found to be the main factors that impact the academic performance of students (Chamorro-Premuzic & Furnham, 2008; Poropat, 2009; Samdal, Wold, & Bronis, 1999). Although intellectual ability highly correlates to the academic performance, it is found that it accounts for less than 50% of the variance in academic performance, which suggests that other factors that contribute to the differences in academic performance must be taken into consideration (Chamorro-Premuzic, 2007).

The main goal of our research is to explore the personality factors other than intellectual ability that contribute to the different educational achievements, and to create a model that can predict the performance and acquired skills based on the subjective factors and perception of the students involved in the learning activities created in our blended learning design. The instructional design created for this study introduced game based learning strategies, videoconference sessions and

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streamed video lessons on Math, Nature/Society and Art classes during one semester of sixth graders. The students were encouraged to take active role in the educational games, to propose their own ideas and take active part in the evaluation process. During the inverted teaching classes students were involved in collaborative activities in order to complete tasks for lessons that were previously given as video streams and learned at home. The synchronous online learning events were organized as videoconference sessions with peers from the other schools.

We use soft computing technique to identify the fuzzy relationships between personality traits, learning style and student's satisfaction as determinant factors on one hand, and academic performance and transferable skills as educational outcomes on the other hand. The Adaptive Neuro Fuzzy Inference System (ANFIS) modeling technique used in our research is suitable for imprecise representation of human reasoning. ANFIS is a Sugeno type inference system able to learn and generate a fuzzy rule base from a given set of input–output data (Jang & Sun, 1995). We also use linear regression model to compare the results with the ANFIS model. The novelty in our approach is that we propose model that is able to make a high accuracy prediction of the educational outcomes of students prior to the actual learning process and regardless to their individual intellectual abilities. In order to verify and compare the results from our ANFIS model, we also construct linear regression model that is a typical statistical model used to predict certain outcomes from independent variables.

This paper is organized in seven sections. Following the Introduction, the second section reviews the literature regarding related work. The third section gives description of the method, including participants, measures and procedure. The fourth section reports the ANFIS model, results, and interpretation of results. The fifth section describes the linear regression models and discusses the obtained results. Comparison between ANFIS and linear regression results, as well as the results from other comparative studies are given in Sections 6 and 7, and the last section concludes the paper and gives brief guidelines for future work.

2. Literature review

Literature exploring factors that influence educational outcomes, finds the intellectual ability, personality and learning approach as significant predictors of the student's academic performance. Besides denoting that these constructs together explain about 40% of the variance in academic performance, the study of Chamorro-Premuzic and Furnham (2008), uses a path analysis approach to explore the relationship among constructs, revealing the mediational effects of personality and learning approaches in the relationship between ability and academic performance. The similar result was confirmed by the study of Furnham, Monsen, and Ahmetoglu (2009), leading to conclusion that the data collected from personality, learning style and ability tests at the beginning of the semester, could reliably predict the school exam results six months later.

Two of the mostly utilized personality theories regarding the correlation of personality and academic performance, are the Eysenck and Big Five personality theory. The Eysenck personality theory recognizes two main personality dimensions i.e. extraversion and neuroticism, and one additional dimension psychoticism (Eysenck, 1958). The Big Five is a wider model recognizing five dimensions of human personality i.e. openness, conscientiousness, extraversion, agreeableness and neuroticism (Costa & McCrae, 1992). The impact of personality traits and learning style on work performance is given in the study of Furnham, Jackson, and Miller (1999). The study involved two hundred participants completing the Eysenck Personality Inventory (EPI) and Mumford's Learning Styles Questionnaire (LSQ) confirming that the personality variables (Neuroticism, Extroversion) and certain learning styles (Reflector, Pragmatist) were significant predictors of the working performance. The meta-analysis of Trapmann, Hell, Hirn, and Schuler (2007) investigates the impact of the Big Five personality factors on academic success of students in higher education. The success was investigated using grades, retention, and satisfaction as different criteria. The study found that Neuroticism is related to academic satisfaction and Conscientiousness correlates with grades. Extraversion, Openness to Experience, and Agreeableness have no significant impact on academic success.

There are many approaches to learning style definition in the literature, following the idea that students learn in diverse ways and prefer different teaching approaches. The researchers report enhancement in learning and performance when students are offered leaning approaches adjusted as to make them comfortable and capable of learning. The study of Hawk and Shah (2007) investigates five learning style instruments (Kolb Learning Style Indicator, Gregoric Style Delineator, Felder–Silverman Index of Learning Styles and the VARK questionnaire) reports their validity, reliability and recommends classroom activities adjusted to the different learning styles of students. The widely recognized Kolb model describes four learning styles: accommodator, diverger, converger and assimilator. The VARK model of learning styles (Fleming, 2006), classifies the learners according to their instructional preferences for giving and receiving information as Visual, Aural, Read/Write and Kinesthetic. The model is shown to be useful to improve the student learning (Marcy, 2001).

In the study of Gurpinar, Alimoglu, Mamakli, and Aktekin (2010), 170 medical students were involved in investigation of the relationship between learning styles, satisfaction with the instruction methods, and academic achievement. The Kolb's model was used in the study to show that in the assimilator group it is possible to predict the satisfaction with traditional training and the academic achievement.

Besides the well-established relationship between ability, personality, learning style and academic performance, the academic attention is further drawn on the impact of subjective perception expressed as satisfaction with the learning process on the academic performance. The perceived satisfaction depends on multiple subjective factors as habits, interests and attitude, relationship with the lecturer and the peers, and environmental factors regarding the classroom environment, use of technology as educational media, content presentation, etc. Educational experience derived from the student's a degree of satisfaction with the courses, instructor's quality of teaching, scholastic achievement, school facilities and school life on one hand and the academic performance on the other, are found to be inextricably related in the study of Chow (2003). Furthermore the student satisfaction is found to be related to the learning environment and learning style. The study of Henry (2008) finds that visual learning style dimension is positively correlated with student's satisfaction in an e-blended course delivery, and negatively correlated in a traditional classroom course delivery mode. The study of Grayson (2004) uses structural equation modeling to build two models: student leniency bias model and teaching effectiveness model, that examine the degree to which program satisfaction is related to professor's performance and the grade point average (GPA). The findings suggest that while there are little relationship between professors' performance and GPA, there is a strong relationship between GPA and the program satisfaction. However, the study suggests that the program satisfaction is directly influenced by certain personality traits that predispose students to evaluate their experiences in a positive manner.

3. Method

3.1. Participants

The case study presented in this research involves 142 K12 students from sixth grade in five primary schools in Republic of Macedonia. 77 of the students were male, and 65 were female. Three schools were from rural and two from non-rural areas of the country.

Table 1
Learning style preferences according to VARK methodology.

Learning style preference	Profile
V	Visual (very strong, strong, mild)
A	Aural (very strong, strong, mild)
R	Read/Write (very strong, strong, mild)
K	Kinesthetic (very strong, strong, mild)
Bimodal	VA, VR, VK, AR, AK, RK
Three modal	VAR, VAK, ARK, VRK
Multimodal	VARK

Table 3
The initial structures of ANFIS-ap and ANFIS-ts.

	ANFIS-ap and ANFIS-ts
No. nodes:	346
No. linear parameters:	168
No. nonlinear parameters:	294
Total no. parameters:	462
No. training data pairs:	500
No. checking data pairs:	352
No. fuzzy rules:	21
No. training epochs:	100

3.2. Input variables

Personality traits Extroversion and Neuroticism are included in our model represented with two input variables. The reason to treat personality with these two constructs was based on few considerations. The Eysenck personality theory originally recognized only Extroversion and Neuroticism dimensions, and was only lately extended with the Psychoticism dimension. The "Big Five", another commonly used personality theory, shares the Extroversion and Neuroticism dimensions with the Eysenck theory, complemented with Openness, Conscientiousness and Agreeableness. Having in mind the age of the participants in our study, we decided to include only the common traits in both theories. We exclude the non-common traits (Psychoticism) presuming that they will not significantly affect the model.

The learning style is represented with four input variables regarding the VARK model that classifies the learners according to their instructional preferences for giving and receiving information, as Visual, Aural, Read/Write and Kinesthetic (Fleming, 2006). The VARK model provides a reliable instrument for examination of learning styles of the participants.

Satisfaction as another valuable construct is also included in the model represented with an input variable.

Although the literature reports few additional significant predictors of the academic success (such as intellectual abilities, and motivation), we limited the exploration on the abovementioned constructs, regarding the following considerations.

The intellectual ability highly correlates to the academic performance, as reported in the work of Chamorro-Premuzic (2007), making it a significant candidate for input construct.

Besides the fact that this correlation is already well reported, our research is aiming towards exploration of the other factors that contribute to the achievement of learner's maximum potential regardless of his/her intellectual abilities. We also contemplated that measuring intellectual abilities results in ranking the intelligence from lesser to higher, which may lead to certain discomfort among young children. After careful consideration, we decided to exclude this construct from the present stage of the study.

Motivation in our study is treated as a factor influencing the overall satisfaction instead of a separate input construct. We considered that providing an instrument for objective measurement of motivation is not trivial for young children. Therefore, it is included in a subsection of the assessment questionnaires estimating the overall satisfaction of learners, as described later in Section 3.2.3.

In the following subsections we give a brief explanation of the input variables with corresponding measurement instruments, included in the present study.

3.2.1. Personality traits

Individual personality traits of participants were evaluated using the short-form Junior Eysenck Personality Questionnaire Revised (JEPQR-S). The JEPQR-S is a 48 item self-reported questionnaire developed by Corulla (1990). It contains four twelve item indices that measure extraversion, neuroticism, psychoticism, and lie scale dimensions of personality. Each item is assessed with a yes/no response, scored as 1 or 0, producing an index for each personality dimension on [1–12] scale.

The Neuroticism and Extroversion personality dimensions are represented by two variables N1 and E3 respectively. The values for the N1 and E3 variables were taken from the scores for neuroticism and extroversion of JEPQR-S questionnaire completed by each student at the beginning of the study.

3.2.2. Learning style

The learning preferences of each participant in the study were evaluated using VARK questionnaire for young people (Fleming, 2006) completed by each student at the beginning of our study. The learning styles according to VARK terminology are classified as Visual, Aural, Reading/Writing, and Kinesthetic/tactile as basic modalities of learning styles. Besides single modality learners that show strong inclination towards particular learning style, the VARK methodology recognizes bi/three/multimodal learners that benefit from multiple learning styles, as given in Table 1.

We defined four learning style variables, V, A, R and K. The learning style of each student is determined from the VARK questionnaire following the VARK methodology. Following the obtained learning style profile, a value from 0 to 6 is assigned to each learning style variable, where 6 denotes very strong affiliation to a single learning modality, 5 = strong, 4 = mild, 3 = bimodal, 2 = three modal, 1 = multimodal, and 0 = no preference in certain modality. For example a learner estimated as Strong Aural learner will obtain the following values for learning style variables: V = 0, A = 5, R = 0, K = 0; bimodal VK profile will

Table 2
List of ANFIS I/O variables.

Variable name	Description	Type	Source	Range of values
N1	Neuroticism	Input	JEPQR-S questionnaire	[1–12]
E3	Extroversion	Input	JEPQR-S questionnaire	[1–12]
V	Visual learning style	Input	VARK questionnaire	[0–6]
A	Aural learning style	Input	VARK questionnaire	[0–6]
R	R/W learning style	Input	VARK questionnaire	[0–6]
K	Kinesthetic learning style	Input	VARK questionnaire	[0–6]]
Sat	Satisfaction	Input	Questionnaire	[1–5]
AP	Academic performance	Output		[1–5]
TS	Transferable skills	Output		[1–5]

Table 4
The performance of ANFIS-ap and ANFIS-ts.

	ANFIS-ap	ANFIS-ts
Training RMSE	0.1795	0.2342
Checking RMSE	0.2132	0.2775
Linear regression RMSE (against checking data)	0.4254	0.5921
Training MAPE	2.0077	3.4984
Checking MAPE	2.8086	4.7905
Training R^2	0.9593	0.9423
Checking R^2	0.9468	0.9272

obtain V = 3, A = 0, R = 0, K = 3 values; three modal VAK profile will obtain V = 2, A = 2, R = 0, K = 2, and multimodal learners will obtain values V = 1, A = 1, R = 1, K = 1.

3.2.3. Satisfaction

The satisfaction with learning process was estimated through age-appropriate Satisfaction Assessment Questionnaires (SAQ) created following the methodology given in Malinovski, Vasileva, and Trajkovik (2014). The SAQ questionnaire consist of nineteen questions divided in five sections constructed to reflect the students' satisfaction regarding the easiness, attitude, motivation, technical and experience regarding the blended educational environment used in the study. The students were providing feedback on each question by giving a score on five-point Likert scale (Likert, 1931). The mean value of the feedback scores from the test was used as overall perceived satisfaction.

3.3. Output variables

3.3.1. Academic performance

The academic performance of each student was evaluated with 1 to 5 grade given by the teachers at the end of the semester. In our educational system, 1 stands for lowest and 5 for highest grade.

3.3.2. Transferable skills

The transferable skills of each student were evaluated with 1 to 5 score by the teacher at the end of the semester. The teachers were observing communication, collaboration and interactivity of each student, and gave an overall opinion score for the student's skills based on their personal assessment.

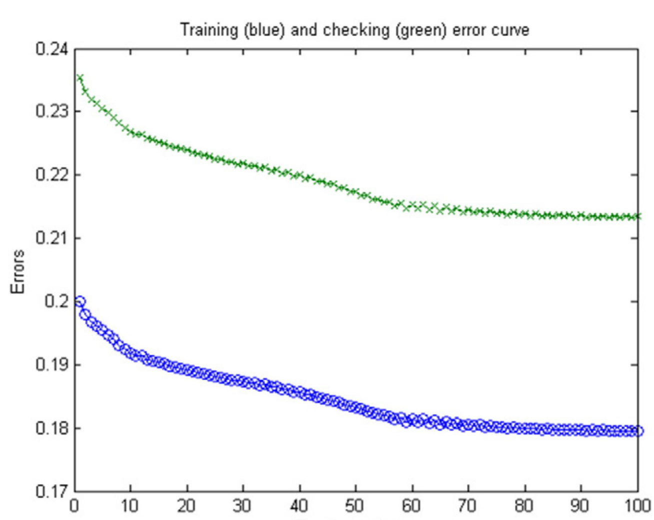

Fig. 1. Training and checking errors from ANFIS-ap.

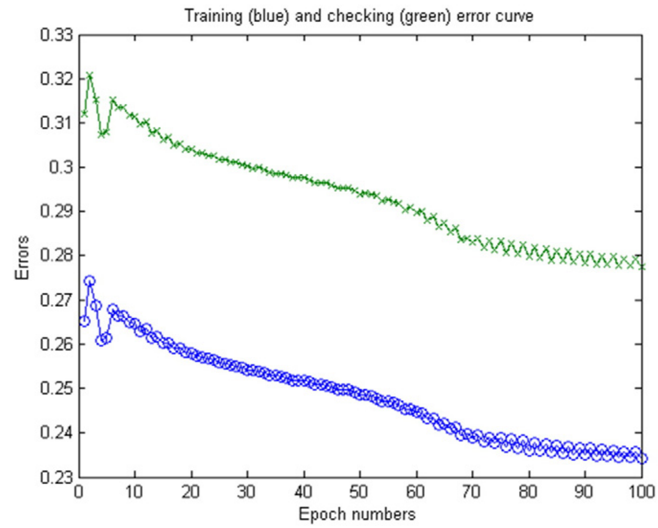

Fig. 2. Training and checking errors from ANFIS-ts.

3.4. Procedure

At the beginning of the semester, the students involved in the study completed JEPQR-S and VARK questionnaires. During the semester, students completed six SAQ expressing their satisfaction with the learning process for each subject (Math, Art and Nature/Society) and both learning setups (traditional and online) included in the study. At the end of the semester, the student's academic performance and transferrable skills were evaluated by teachers.

4. ANFIS model

4.1. ANFIS theory

ANFIS is a hybrid neuro-fuzzy system that integrates the ability of neural networks to learn from sample data, and the fuzzy logic ability to represent human knowledge (Jang & Sun, 1995). The structure of the system consists of five layers, each having different types of nodes connected with the nodes from the previous level. The input signals to each node are coming from the output signals in the previous level. The rule base consists of Takagi–Sugeno type rules. Its complexity

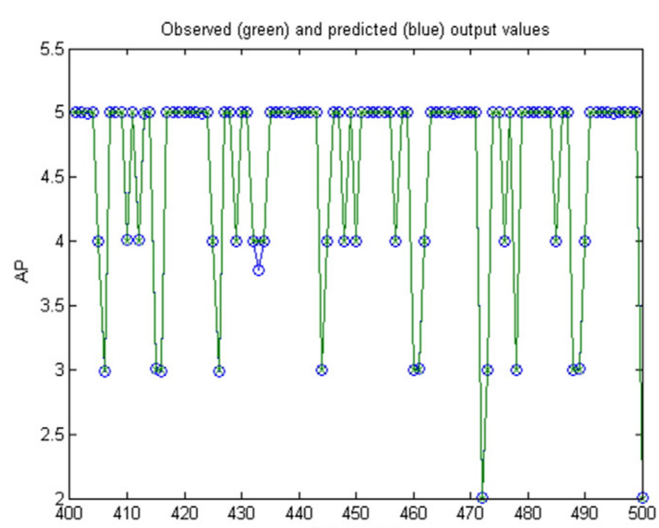

Fig. 3. Comparison of actual and predicted output values from ANFIS-ap.

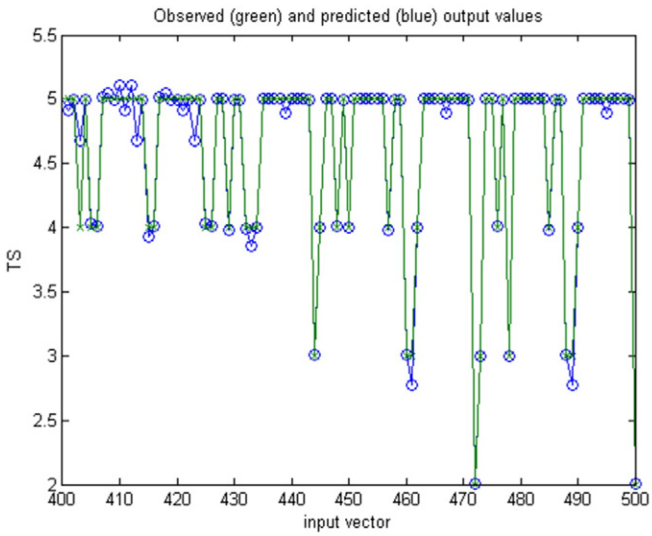

Fig. 4. Comparison of actual and predicted output values from ANFIS-ts.

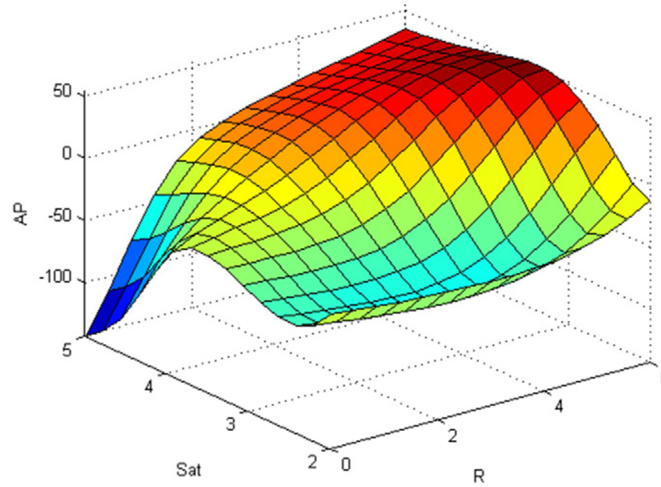

Fig. 6. Effect of Sat and R on AP.

depends on the number of input variables and the number of values in term sets. A typical rule in a system with two input and one output variables is represented as:

Rule i : if x_1 is A_i and x_2 is B_i then $f_i = p_i x_1 + q_i x_2 + r_i$.

The parameters of the membership functions are tuned in learning cycles that can employ either back-propagation or hybrid learning algorithm. The hybrid algorithm is a combination of back-propagation and Least Square Error (LSE) algorithm. It uses two-pass learning cycle, a forward and a backward pass. In the forward pass LSE algorithm is used to tune the consequent parameters in fuzzy rules. In the backward pass, the premise parameters of the rules are tuned using a back-propagation algorithm (usually Gradient Descent).

4.2. Design of the ANFIS systems for AP and TS prediction

We constructed two ANFIS models: ANFIS-ap to predict the academic performance (AP) and ANFIS-ts to predict transferable skills (TS). The systems were defined, initialized and trained using Matlab Fuzzy Logic Toolbox. Both systems use the same input variables, while outputting the AP and TS variables.

The complete list of I/O variables is given in Table 2.

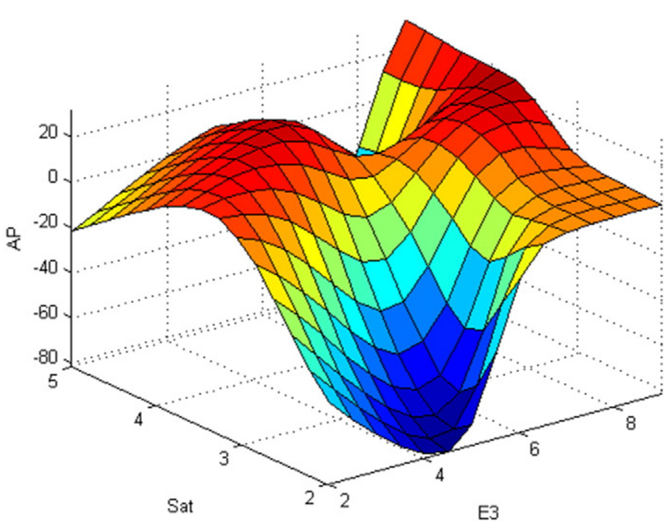

Fig. 5. Effect of Sat and E3 on AP.

The complete I/O data set of 852 vectors was obtained from the evaluation of 142 students, participating in the case study involving three subjects (Math, Art and Nature/Society) in two learning setups (traditional and online). The initial I/O data set was randomly divided into training data set (500 vectors) and checking data set (352 vectors).

4.3. Initialization of the system structure and training the ANFIS

The systems were initialized using subtractive clustering algorithm and trained in 100 epochs with 0 error tolerance. The training process stops when the training error becomes less than the predefined error tolerance, or after the number of training epochs is reached. When the training process is finished, the initial membership functions which best suit the training data are identified and the model is ready for use.

The initial structure of ANFIS systems is given in Table 3.

4.4. Evaluation of the system performance

Model validation is performed to evaluate how well the model predicts the output values of the corresponding data set. Model validation is a process in which only the input vectors from the training and checking data sets are presented to the trained FIS model, to see how well the model predicts the corresponding data set output value. The checking data set is used to test the fitness of the obtained model.

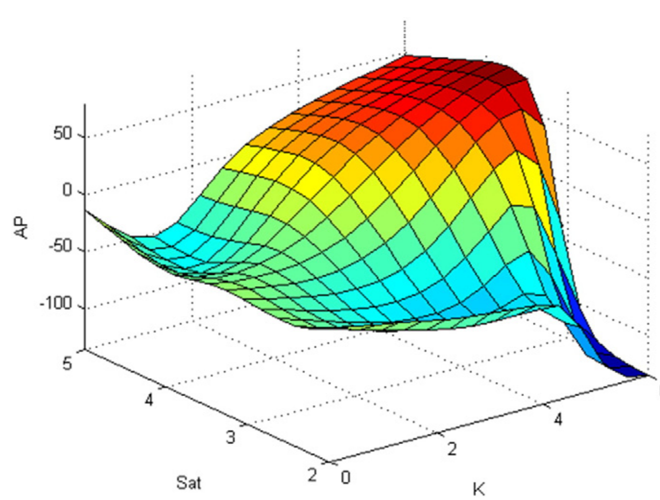

Fig. 7. Effect of Sat and K on AP.

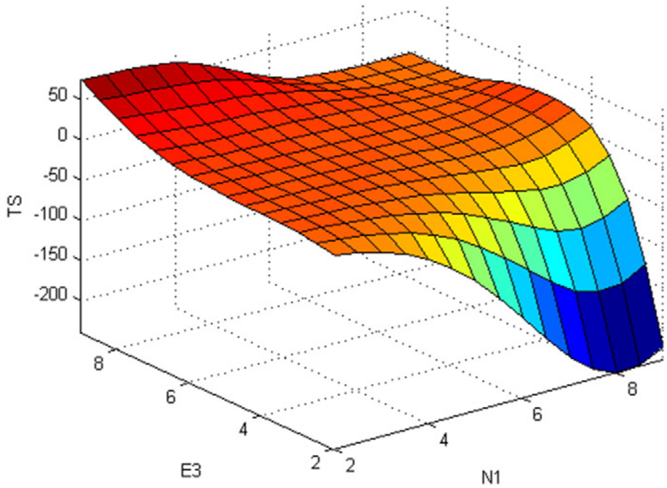

Fig. 8. Effect of N1 and E3 on TS.

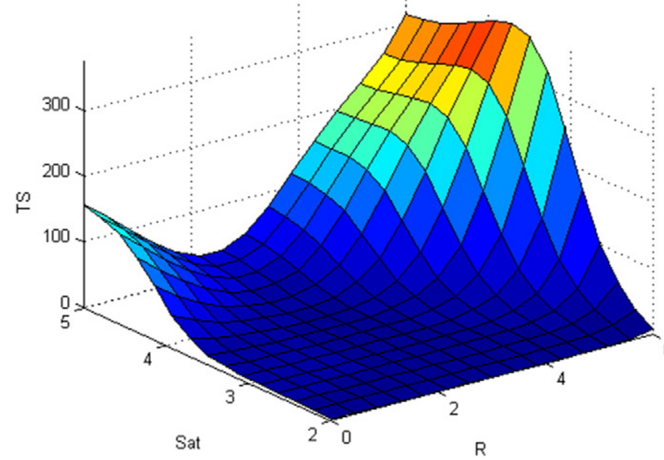

Fig. 10. Effect of Sat and R on TS.

4.5. ANFIS results and discussion

The performance of the ANFIS-ap and ANFIS-ts are estimated using Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Coefficient of Determination (R^2) measures.

RMSE, MAPE and R^2 are defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_p(i) - Q_o(i)\right)^2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Q_p(i) - Q_o(i)}{Q_o(i)}\right| \times 100$$

$$R^2 = 1 - \frac{SSres}{SStot} \quad \text{where} \quad SSres = \sum_{i=1}^{n}\left(Q_o(i) - Q_p(i)\right)^2;$$
$$SStot = \sum_{i=1}^{n}\left(Q_o(i) - \overline{Q_o(i)}\right)^2.$$

$Q_p(i)$ and $Q_o(i)$are predicted and observed values respectively, and $\overline{Q_o(i)} = \frac{1}{n}\sum_{i=1}^{n} Q_o(i)$.

The results for ANFIS-ap and ANFIS-ts are given in Table 4.

The results show that both ANFIS-ap and ANFIS-ts models produce lower checking RMSE compared to the RMSE of linear regression against checking data. They also produce rather high R^2 values explaining approximately 94% variance for AP and 92% variance for TS. These results proved that ANFIS models are appropriately constructed offering good prediction results for AP and TS variables.

The error curves of ANFIS-ap and ANFIS-ts are given in Figs. 1 and 2 respectively. The error curves remain stable after around 100 epochs of training. When error curves start to rise, it signalizes model over fit. Therefore 100 epochs of training are considered optimal in our model.

The comparison of actual and predicted output values from ANFIS-ap and ANFIS-ts are given in Figs. 3 and 4 respectively.

The effects of the input parameters on the AP are depicted by the ANFIS-ap surfaces given in Figs. 5, 6, and 7 respectively. The surfaces are obtained by varying two parameters and keeping the other two fixed. The surface in Fig. 5 shows that the best AP results are obtained for higher values of Sat and E3 variables. However, the surfaces in Figs. 6 and 7 show the difference in AP of Read/Write and Kinesthetic learners. While the stronger Read/Write learners produce higher AP, the stronger Kinesthetic learners produce lower AP values regardless of personality traits and satisfaction. This result gives a good indication that this learning setup is not best suited for Kinesthetic learners, and therefore it is desirable to consider alternative pedagogical approach for these learners for better results.

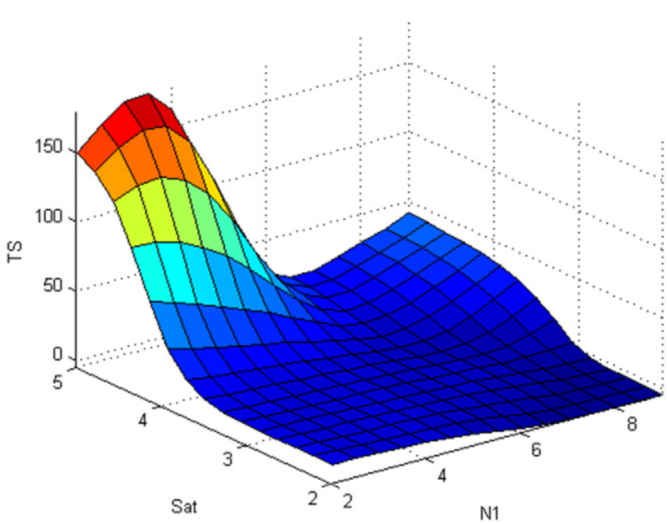

Fig. 9. Effect of N1 and Sat on TS.

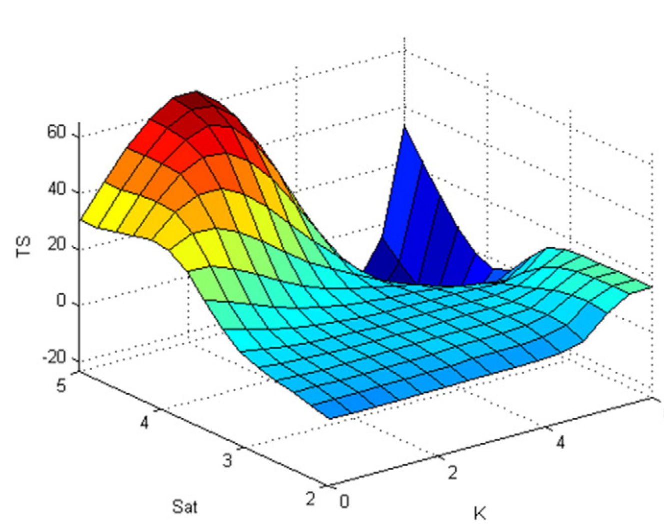

Fig. 11. Effect of Sat and K on TS.

Table 5
The linear regression models LR-ap and LR-ts.

	LR-ap	LR-ts
Independent variables	N1, E3, V, A, R, K, Sat	N1, E3, V, A, R, K, Sat
Dependent variable	AP	TS
Regression equation	$AP = a^*N1 + b^*E3 + c^*V + d^*A + e^*R + f^*K + g^*Sat + h$	$TS = a^*N1 + b^*E3 + c^*V + d^*A + e^*R + f^*K + g^*Sat + h$
F-value (ANOVA)	526.509	275.779
p-Value (ANOVA)	0.000	0.000
RMSE	0.39248	0.46069
R^2	0.814	0.696

The effects of the input parameters on the TS are depicted by the ANFIS-ts surfaces given in Figs. 8, 9, and 10 respectively. The surfaces in Figs. 8 and 9 show that the high values in neuroticism produce low values in transferable skills regardless of the other factors, which is a rather expected result.

The surfaces in Figs. 10 and 11 depict the difference between Read/Write and Kinesthetic learners. While Read/Write learners produce high values for TS when values for Satisfaction are also high, Kinesthetic learners produce low values for TS even when values for Satisfaction are high.

5. Linear regression model

5.1. Design of the linear regression models

Linear regression model is a statistical approach used to explore the correlation between input variables and educational outcomes. We constructed two linear regressions, LR-ap having the academic performance (AP) as dependent variable, and LP-ts having the transferable skills (TS) as dependent variable, in order to compare the performance of ANFIS and linear regression models. The regression models with the corresponding RMSE and R^2 are given in Table 5.

5.2. Linear regression results and discussion

The effect of the independent variables (predictors) on the resulting AP and TS can be studied using t-statistics and their associated 2-tailed p-values. The null hypothesis tested with the t-statistics states that given regression coefficient is equal to zero at alpha level of 0.05. When regression coefficient is zero it means that the corresponding variable has no effect on the model. The results are given in Table 6.

The results show that E3, V, R and Sat variables have significant effect on the model for AP prediction. The N1, E3, R, K and Sat variables have significant effect on the model for TS prediction.

The Pearson correlation coefficients among personality traits (N1, E3), learning styles (V, A, R, K), satisfaction and educational outcomes (AP and TS) are given in Table 7. The results indicate that the AP and TS are positively correlated to Extroversion, Satisfaction and Visual, Aural and Read/Write learning styles, but negatively correlated to Neuroticism and Kinesthetic learning style, at alpha level of 0.05.

The results indicate that the Satisfaction is the strongest predictor of the AP and TS in the linear regression models. However Extroversion personality trait (E3) is also a significant predictor of both educational outcomes, while Neuroticism (N1) impacts the student's transferrable skills but does not have significant impact on the academic performance. The correlation matrix shows negative correlation between kinesthetic learning style (K) and educational outcomes. The correlation between kinesthetic learning style (K) and satisfaction is also negative. The correlation matrix further reveals that Read/Write (R) learners have the strongest correlation with the educational outcomes and satisfaction, compared to the other three learning styles. These results are in line with the results from ANFIS models regarding the influence of different learning styles on educational outcomes.

When all the input variables are included, the linear regression models explain about 81% of variance of AP and 69% of variance in TS.

6. Comparison between ANFIS and linear regression models

The RMSE of regression models LR-ap (0.3924) and LR-ts (0.4606), are higher than the RMSE of corresponding ANFIS-ap (0.2132) and ANFIS-ts (0.2775) models. On the other hand the R^2 of LR-ap (81%) and LR-ts (69%), are lower than the R^2 of corresponding ANFIS-ap (94%) and ANFIS-ts (92%) models. These results give a clear indication that the ANFIS models outperform the linear regression models and therefore are better choice for AP and TS prediction.

The other results of both models are compatible. Both models indicate that the satisfaction is the strongest predictor of the educational outcomes. The impact of extroversion personality traits is significant on both educational outcomes, while neuroticism has negative effect on transferrable skills and no significant effect on academic performance. The results regarding the impact of different learning styles on educational outcomes indicate that Read/Write learners would mostly benefit from the blended educational setup used in our case study, while Kinesthetic learners benefit at least.

7. Comparison with other studies

The relationship between personality, learning style, cognitive ability and the academic performance is widely studied in the literature. The models for academic performance prediction are usually based on Linear Regression and Structured Equation Modeling (SEM). The study of Duff, Boyle, Dunleavy, and Ferguson (2004) explores the impact on Big Five personality traits, approaches to learning, and some background variables of age, gender and prior educational achievement on

Table 6
The t-statistics on LR-ap and LR-ts coefficients.

		LR-ap			LR-ts		
Variable	Reg. coefficient	Coefficient value	t-Value	p-Value	Coefficient value	t-Value	p-Value
(Constant)	h	−0.491	−3.557	0.000	1.188	7.330	0.000
N1	a	0.004	0.505	0.614	−0.040	−3.881	0.000
E3	b	0.043	5.856	0.000	0.025	2.847	0.005
V	c	0.053	0.119	0.002	0.020	0.987	0.324
A	d	0.024	1.641	0.101	0.017	1.006	0.315
R	e	0.057	3.922	0.000	0.065	3.766	0.000
K	f	−0.017	−1.045	0.296	−0.068	−3.646	0.000
Sat	g	0.976	52.039	0.000	0.744	33.807	0.000

Table 7
Correlations among personality traits (N1, E3), learning style (V, A, R, K), satisfaction (Sat) and educational outcomes (AP and TS).

	AP/TS	N1	E3	V	A	R	K	Sat
AP/TS	1	−0.103/−0.199	0.184/0.160	0.056/0.057	0.117/0.135	0.270/0.326	−0.429/−0.503	0.890/0.793
N1		1	−0.192	−0.271	−0.119	−0.008	0.340	−0.069
E3			1	0.094	0.085	−0.098	−0.153	0.107
V				1	−0.070	−0.323	−0.289	0.008
A					1	−0.267	−0.363	0.113
R						1	−0.419	0.227
K							1	−0.366
Sat								1

academic performance. The structural equation modeling used in the study finds that the personality factor accounts for up to 43.6% of the variance in performance, while the linear regression model having academic performance as dependent variable, and the age, prior educational achievement and consciousness personality dimension as independent variable, accounted for up to 24.1% of the variance in performance. When all the variables are included in the regression model, the prediction of the academic performance variance was 34.2%.

The study of Chamorro-Premuzic and Furnham (2008) includes the intellectual ability besides personality and learning approaches in the model as a strong predictor of the academic performance. Together the variables explained 40% of the variance in AP.

The model presented in our study uses ANFIS and linear regression modeling to predict academic performance and transferrable skills, from the personality traits (Neuroticism and Extroversion), Learning style (Visual, Aural, Read/Write, Kinesthetic), and Satisfaction with the learning process. The models were built from the data collected during the cases study conducted according to the blended educational setup proposed in our research. The four variables ANFIS models explained approximately 94% of variance in academic performance and 92% of transferrable skills.

The results in our study are competitive with the results from the previous studies, not only in the prediction accuracy of the models, but also regarding the impact on transferrable skills as a valuable educational outcome in the modern educational approaches.

8. Limitations on the study

Although the present study was carefully designed, several limitations should be taken into account. The first limitation refers to the sampling of students. Selecting a larger number of students of different ages might give a better insight into the differences in learning styles and its implication to the academic success. Second, the personality traits are treated only with the Neuroticism and Extroversion constructs. Extending the personality traits with Openness, Conscientiousness and Agreeableness from the “Big Five”, as well as including other constructs as motivation, self-control, etc. might give us some additional significant information of the correlations between individual differences and educational outcomes. Third, the transferable skills are treated as overall estimation of the student's skills based on the teacher observations. Treating the skills separately and providing a tool that would measure them more objectively rather than subjectively, would be beneficial in understanding the relationship between the input constructs and the separate skills. Lastly, the blended educational scenario might be extended and adapted with variety of other contents in order to obtain more general conclusions in various educational contexts.

9. Conclusion

This paper investigates the impact of personality, learning style and satisfaction on certain educational outcomes, namely the academic performance (AP) and transferrable skills (TS) generally covering student's communication, collaboration and interactivity. We constructed two ANFIS models that outcome AP and TS, and two corresponding linear regression models. The promising results of 94% and 92% prediction accuracy of ANFIS models, suggest that neuro-fuzzy techniques provide better prediction of educational outcomes compared to the statistical models. Having the well reported positive correlation of cognitive abilities and academic performance in the literature, this paper investigates the other factors including personality, learning style and satisfaction that contribute to explanation of the variance in academic performance and acquired skills. The results are obtained from evaluation and observation of students participating in an appropriately tailored blended learning scenario. Further investigation of the model should be directed towards inclusion of larger number of participants, broader range of ages, and different educational setups. Investigation on the effects of inclusion of other predictors in the model is also an interesting perspective for future work.

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References

Chamorro-Premuzic, T. (2007). *Personality and Individual Differences*. Blackwell Publishing.
Chamorro-Premuzic, T., & Furnham, A. (2008). Personality, intelligence and approaches to learning as predictors of academic performance. *Personality and Individual Differences*, *44*(7), 1596–1603.
Chow, H. P. (2003). Exploring the predictors of educational experience and academic performance among university students in Regina. *Alberta Journal of Educational Research*, *49*(1), 101–105.
Corulla, W. J. (1990). A revised version of the psychoticism scale for children. *Personality and Individual Differences*, *11*(1), 65–76.
Costa, P. T., & McCrae, R. R. (1992). *Professional manual: Revised NEO personality inventory (NEO-PI-R) and NEO five-factor inventory (NEO-FFI)*. Odessa, FL: Psychological Assessment Resources.
Duff, A., Boyle, E., Dunleavy, K., & Ferguson, J. (2004). The relationship between personality, approach to learning and academic performance. *Personality and Individual Differences*, *36*(8), 1907–1920.
Eysenck, H. J. (1958). A short questionnaire for the measurement of two dimensions of personality. *Journal of Applied Psychology*, *42*(1), 14.
Fleming, N. (2006). *Teaching and learning styles — VARK strategies*. Christchurc, NewZealand: Microfilm, Ltd.
Furnham, A., Jackson, C. J., & Miller, T. (1999). Personality, learning style and work performance. *Personality and Individual Differences*, *27*(6), 1113–1122.
Furnham, A., Monsen, J., & Ahmetoglu, G. (2009). Typical intellectual engagement, Big Five personality traits, approaches to learning and cognitive ability predictors of academic performance. *British Journal of Educational Psychology*, *79*(4), 769–782.
Grayson, J. P. (2004). The relationship between grades and academic program satisfaction over four years of study. *Canadian Journal of Higher Education*, *34*(2).
Gurpinar, E., Alimoglu, M. K., Mamakli, S., & Aktekin, M. (2010). Can learning style predict student satisfaction with different instruction methods and academic achievement in medical education? *Advances in Physiology Education*, *34*(4), 192–196.
Hawk, T. F., & Shah, A. J. (2007). Using learning style instruments to enhance student learning. *Decision Sciences Journal of Innovative Education*, *5*(1), 1–19.
Henry, P. D. (2008). Learning style and learner satisfaction in a course delivery context. *International Journal of Humanities & Social Sciences*, *2*(2).
Jang, J. S. R. C., & Sun, T. (1995). Neuro-fuzzy modeling and control. *Proceedings of the IEEE Issue Date: Mar 1995* (pp. 378–406).
Kain, D. J. (2003). Teacher-centered versus student-centered: Balancing constraint and theory in the composition classroom. *Pedagogy*, *3*(1), 104–108.

Likert, R. (1931). *A technique for the measurement of attitudes. Archives of Psychology*. New York: Columbia University Press.
Malinovski, T., Vasileva, M., & Trajkovik, V. (2014). Integrating computer games in primary education for increased students' QoE. *ICT Innovations 2013* (pp. 35–44). Springer International Publishing.
Marcy, V. (2001). Adult learning styles: How the VARK Learning Styles Inventory can be used to improve student learning. *Perspectives on Physician Assistant Education*, *12*(2), 117–120.
Osguthorpe, R. T., & Graham, C. R. (2003). Blended learning environments: Definitions and directions. *Quarterly Review of Distance Education*, *4*(3), 227–233.
Poropat, A. E. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*(2), 322.
Samdal, O., Wold, B., & Bronis, M. (1999). Relationship between students' perceptions of school environment, their satisfaction with school and perceived academic achievement: An international study. *School Effectiveness and School Improvement*, *10*(3), 296–320.
Trapmann, S., Hell, B., Hirn, J. O. W., & Schuler, H. (2007). Meta-analysis of the relationship between the Big Five and academic success at university. *Zeitschrift für PsychologieJournal of Psychology*, *215*(2), 132–151.