Applied Soft Computing 34 (2015) 129–138

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

An ANFIS model of quality of experience prediction in education

Tatjana Vasileva-Stojanovska*, Marina Vasileva, Toni Malinovski, Vladimir Trajkovik

Faculty of Computer Science and Engineering, Ss. Cyril and Methodius University, Skopje, Rugjer Boshkovik bb, PO Box 574, 1000 Skopje, Yugolav Republic of Macedonia

ARTICLE INFO

Article history:
Received 18 January 2014
Received in revised form
28 November 2014
Accepted 26 April 2015
Available online 5 May 2015

Keywords:
Quality of Experience
Learning style
ANFIS

ABSTRACT

This paper presents a Quality of Experience (QoE) prediction model in a student-centered blended learning environment, equipped with appropriate technologically enriched classroom. The model uses ANFIS technique to infer the QoE from the individual subjective factors and the objective technical factors which altogether influence the perceived QoE. We explored the influence of subjective personality traits extroversion and neuroticism, as well as the learning style on QoE. The objective factors included in the model are technically measurable parameters latency, jitter, packet loss and bandwidth affecting Quality of Service (QoS) of the underlying technology. The findings presented in this paper are obtained from a case study which involved 8 teachers and 142 students from second and sixth grade in five primary schools in the Republic of Macedonia. The teachers involved in the project introduced game-based learning strategies in classes, including on-line videoconferences, streamed video content and classical face to face gaming. We constructed three ANFIS systems with seven and four input variables and compared their performances using the RMSE, MAPE and R^2 measurements. The results showed that perceived QoE can be reliably predicted by the student's personality traits and learning style as subjective factors and network jitter as an objective factor.

© 2015 Elsevier B.V. All rights reserved.

1. Introduction

Education is an interactive process during which students gradually adopt knowledge, develop intelligent reasoning, judgment and skills needed for successful mature life. The subjective perception of the process by the involved participants can be expressed as a level of satisfaction. The student satisfaction with the educational process directly influences his academic performance [34]. Therefore, constant efforts are made to approximate and adapt the educational process and environment to the student's preferences, in order to ensure optimal performance for each individual. From the pedagogical point of view, the shift from classical teacher-centered toward student-centered educational models, brings the individual preferences and learning style at the center of the educational process and creates optimal environment for learners to develop their real potential.

When the educational process is aided by technology or product, the subjective measure of satisfaction is expressed as "Quality of Experience" (QoE). According to ITU-T P.10/G.100, QoE is defined as the overall acceptability of an application or service, as subjectively perceived by the end-user. Therefore, QoE derives from the complete system's effect on the user, influenced by the underlying technology as well as the user expectations and context. Having in mind the subjective nature of QoE, it is understandable why its quantification and measurement is not trivial. The literature reports multiple efforts attempting to approach the concept of QoE in terms of user perception, expectation and experience [33,35]. Classical example is the approach described by ITU-T Focus Group on IPTV in 2008 [16] which measures QoE through appropriate user tests and surveys while expressing QoE values in terms of Mean Opinion Score (MOS).

Even though the MOS method delivers the goal of subjective quality measurement, its major drawback is the low cost effectiveness. Therefore various attempts are made to "objectify" i.e. to correlate the QoE with certain parameters that can be objectively measured [25]. These parameters are classified and referred as the quality of network while delivering the service to the users (jitter, delay, packet loss, etc.) and the quality of delivered content (visual quality, audio quality, audio delay etc.). The first class of parameters quantifies a measure known as Network Quality of Service (NQoS)

* Corresponding author at: Rugjer Boshkovik bb, PO Box 574, 1000 Skopje, Yugolav Republic of Macedonia. Tel.: +389 75 599 536.
E-mail addresses: tatjanav@nbrm.mk (T. Vasileva-Stojanovska), vasileva_marina@yahoo.com (M. Vasileva), tmalin@nbrm.mk (T. Malinovski), trvlado@finki.ukim.mk (V. Trajkovik).

http://dx.doi.org/10.1016/j.asoc.2015.04.047
1568-4946/© 2015 Elsevier B.V. All rights reserved.

Table 1
QoS provisioning for interactive and streaming video.

	Interactive video	Streaming video
Packet loss	<1%	<5%
Latency (one way)	<150 ms	<4–5 s
Jitter	<30 ms	No significant requirements
Bandwidth	Overprovision the minimum-priority bandwidth guarantee to the size of the videoconferencing session plus 20 percent	Depends on the encoding format and rate of the video stream

and the second class of parameters quantifies the Application Quality of Service (AQoS). Together NQoS and AQoS comprise an overall objective measure of the network performance known as Quality of Service (QoS).

According to ITU-T E.800 [16], QoS is defined as the collective effect of performance which determines the degree of satisfaction of the end-user of a certain service. By contributing to the improvement of overall performance of the network, the QoS management improves the end-user experience with the system. System vendors provide various mechanisms for QoS management and provision, assuring that QoS in given network setup can be controlled and guaranteed in advance.

Earlier studies on QoS to QoE correlation have shown that the network level QoS parameters have bigger impact on perceived QoE than the application level QoS parameters [21,35]. Therefore in our research activities we have mainly focused on the NQoS provisioning parameters, as objective factors which influence student's QoE.

The recommendations given in the guidelines for QoS provisioning for interactive and streaming video [15] are summarized in Table 1.

Following the study of Calyam et al. [3], the values of the NQoS parameters are mapped to MOS values as given in the Table 2.

Besides the delivered QoS, the personal affinities have strong impact on the perceived QoE as well. In attempt to identify the main subjective factors affecting QoE in a blended educational environment, we found strong support in literature reporting the personality and learning style as leading factors on the student's academic performance in the classical education [2,5,7]. Personality factors (Extroversion, Neuroticism) as given in Eysenck theory [10] and certain learning styles (Reflector, Pragmatist) were statistically significant predictors of rated performance in the study of Furnham et al. [12]. Furthermore, the literature reports strong relationship between student satisfaction and academic performance [6,32], which gives a solid reason to explore the effect of personality traits and learning style on the student satisfaction as well.

The main goal of this paper is to explore the objective and subjective factors influencing and predicting the perceived student's QoE in a blended educational environment, particularly in technology aided classrooms involving videoconference (VC) and video streaming (VS) sessions in the educational process. Furthermore, having in mind the importance of satisfaction on the overall academic performance, our aim is to identify stereotypes of students depending on their personality and preferences, and offer adaptive educational scenarios to the different stereotypes, thus ensuring optimal learning environment for each particular individual. For that purpose, in our case study we involved eight teachers and 142 students from second and sixth grade in five primary schools in Republic of Macedonia. We created educational scenario in which certain parts of Math, Nature/Society and Art curricula were held in inverted student-centered manner in which students were playing games, participating in videoconference sessions and watching streamed video lessons. The choice of the sample of students to participate in this study was based on few criteria: the age of the children had to be appropriate to apply the personality tests (8–18 years old); having in mind that the resulting sample should explain QoE for a broader range of primary school students and the game based learning scenarios are considered to motivate mostly the younger children, we decided to include children from different ages yet young enough to be motivated by the given scenario. The teachers involved in the project had to be properly trained to apply the given educational scenario on the classes. The schools were chosen from both rural and non-rural areas of the country. The participants were able to express themselves through the game, to collaborate with the other students in order to complete some task, and even participate in the process of evaluation. The teacher's role was to present the objectives and to mediate, support and motivate participants. The students were learning curricula topics by playing two social games for Nature/Society classes, two logical games for Math classes and two visual games for Art classes. Every game was played in three subsequent school classes having different educational setup appropriate for each class. First class was held in a traditional face to face manner, second class involved videoconference session with peers from another school, and in the third class the students were completing tasks following instructions given previously in a streamed video session. At the end of the study, the students have completed total of 18 Math, Nature/Society and Art classes, by playing six different games in three different educational setups: a classical face to face classroom class, a videoconference session class and a video streaming session class. At the end of each class students filled a questionnaire rating the aspects of satisfaction, content, simplicity, technical setup, approach and eagerness to repeat the class experience [29].

The videoconferencing infrastructure used in our case study is based on a Polycom videoconferencing platform, which connects different locations in several primary, high schools and universities in Macedonia, with Skopje as a central site. These sites are interconnected through the MARNET (Macedonian Academic and Research Network) networking infrastructure which connects university campuses and other state educational institutions, including most of the involved primary schools. Since the schools in rural areas did not have access to this network, they used the Internet as a

Table 2
NQoS parameters to MOS mappings for VC and VS.

	Videoconference (VC)			Video streaming (VS)		
	Good	Acceptable	Poor	Good	Acceptable	Poor
MOS	4–5	3–4	<3	4–5	3–4	<3
Latency	0–150 ms	150–300 ms	>300 ms	0–3 s	3–5 s	>5 s
Packet loss	0–0.5%	0.5–1.5%	>1.5%	0–3%	3–5%	>5%
Jitter	0–20 ms	20–50 ms	>50 ms	0–1 s	1–4 s	>4 s

connection to the videoconferencing platform, thus allowing us to perform analysis on different networking conditions. Each remote classroom was equipped with teacher/student camera, appropriate displays, proper sound systems and interconnecting devices to the videoconferencing platform. The systems includes central management center placed at the central site, for global, centralized view of all videoconferencing endpoints and network elements, while enabling monitoring, maintenance and real-time control. The videoconferencing endpoints participated as a closed user-group based on H.323 protocol, while employing H.264 standard for video format, Siren22 audio codec and up to 1920 kbps call rate. Through the centralized management we were able to monitor the sessions and gather real time feed from instruments and sensors, including the necessary NQoS parameters for bandwidth, packet loss, latency and jitter.

In order to investigate the perceived QoE of the students involved in our case study, and develop a model that would predict the QoE of the future students participating in similar blended educational setups, we used an Adaptive Neuro Fuzzy Inference System (ANFIS) which is able to learn and generate a fuzzy rule base from a given set of input–output data [19]. ANFIS is a Sugeno type fuzzy inference system that uses back propagation or hybrid algorithm to tune the membership functions in fuzzy variables of fuzzy rules. The use of ANFIS as modeling technique empowers the system with the ability to learn from the I/O data, and strong knowledge representation through the fuzzy rule base. The novelty in our approach is that we introduce subjective factors (personality related: neuroticism, extroversion; and learning style) together with the objective technical factors (QoS related: packet loss, latency, jitter) as input parameters to the ANFIS, to find the fuzzy relation with the QoE which is an output parameter from the system [38].

This paper is organized in eight sections. After introduction, Section 2 reviews the literature regarding related work. Section 3 gives a brief description of the ANFIS theory. The ANFIS design and experiments for QoE prediction is given in Section 4. Section 5 reports the results, analysis and interpretation of the results. Comparison of proposed ANFIS models with linear regression and other prediction models is given in Section 6, and Sections 7 and 8 give some brief guidelines for future work and conclude the paper.

2. Literature review

The academic research recognizes two main approaches for QoE assessment, classified as subjective and objective. The standard subjective approaches use MOS method, based on user response regarding the experienced service. Recognizing the contribution of the user expectations in the QoE assessment, the study of Egger et al. [8] proposes a methodology that extends the standard MOS metric, including the conversational interactivity as a characteristic of the expectation dimension in QoE assessment, and the social presence indicator. A framework for video QoE inference based on MOS rating in real time is given in [39]. The framework was initially constructed using bitrate, latency and packet loss as input parameters to predict the QoE, and compared the results with the obtained MOS values from survey filled by the users. The obtained error rate from predicted to actual MOS value varied from 0.4 to 4%.

The main drawback of MOS related approaches is that they tend to be expensive and time-consuming which makes them low cost-effective. The objective approaches, designed to overcome the cost-effectiveness limitation of MOS method, are using quantitative measurements of signals or network parameters in attempt to obtain correlation between those parameters and the perceived QoE. Some of the common proposed metrics are Peak Signal to Noise Ratio (PSNR), Video Quality Metric (VQM), Structural Similarity Index (SSIM), etc. [25]. A methodology for quantification of the correlation between QoS and QoE is given in [40]. Some approaches are using combination of both methodologies in order to overcome the drawbacks of each individual approach. EvalVid framework is designed to evaluate the quality of transmitted video over network. It measures the network QoS parameters and calculates the PSNR of the received video. Furthermore, the framework offers a tool for conversion of the PSNR to MOS, attempting to map the objective calculations to subjective score [24].

A systematic literature survey of 44 empirical studies of QoE is given in Mintauckis master's thesis [31]. The main focus of the thesis is to categorize the QoE research by subject, type of study, aspects, purpose and results. The findings indicate that the "satisfaction" was considered as the vital aspect regarding QoE assessment. The next most evaluated aspect was "loss/packet loss", which belongs to the aspect group "network QoS".

Having the presumption that the "satisfaction" and "network QoS" are the main aspects affecting the overall students' QoE in a blended educational environment we researched the literature to find support and investigate the factors influencing the above mentioned aspects.

The student satisfaction with the educational process has been drawing academic attention not only regarding the improvement of scores and academic performance, but also regarding the aspects of persistence and student retention in the educational process. Therefore there are constant efforts in the academic community to identify and improve the factors affecting the student satisfaction and provide optimal educational environment leading to maximum effectiveness and results for each individual learner. The factors vary from personal affinities regarding the learning style, personality components including habits, interests and attitude, relationship with the lecturer and the peers, to environmental factors regarding the classroom environment, use of technology as educational media, content presentation, etc. The relationship between student satisfaction and learning outcomes in an e-learning environment is given in [9].

Learning style is recognized as one of the key factors influencing perceived satisfaction of students with educational process [13]. Although literature recognizes many definitions of learning style, the simplest definition given by Grasha [17] defines a learning style as an individual's preferred way of learning. One of the many approaches for Learning Styles (LS) assessment, designed to measure instructional preferences for giving and receiving information, is the VARK methodology developed by Neil Fleming [11]. The learning styles according to VARK terminology are classified as Visual, Aural, Reading/Writing, and Kinesthetic/Tactile as basic modalities of learning styles. Some learners are strongly inclined toward a single modality, but majority of learners benefit from all learning modalities.

In the study of Gurpinar et al. [14], 170 medical students were involved in investigation of the relationship between learning styles, satisfaction with the instruction methods, and academic achievement. The study used the Kolb's model recognizing four learning styles: Accommodator, Diverger, Converger and Assimilator. The study showed that in the assimilator group it is possible to predict the satisfaction with traditional training and the academic achievement. Assessment of the influence of personality and learning style on work performance is given in [12]. The study involved two hundred participants completing the Eysenck Personality Inventory (EPI) and Mumford's Learning Styles Questionnaire (LSQ) and confirmed that the personality variables and certain learning styles were significant predictors of the working performance.

Besides the learning style, the other key component which determines student perception and success in education is his personality traits. The Eysenck personality theory [10] recognized three main personality dimensions: Neuroticism (N), Extroversion

(E) and Psychoticism (P). The combinations of different ranges of dimensions define a personality wheel divided in four quadrants marking the personality as sanguine, choleric, phlegmatic or melancholic. HANES – scale of Neuroticism and Extroversion for children and youth, is adapted version of Eysenck Personality Inventory (EPI) for young people from 8 to 18 years old [1]. The HANES methodology uses two questionnaires HANES-1 and HANES-2, having 36 and 32 questions respectively, used to evaluate the personality traits Neuroticism (N1), Extroversion (E3 which incorporates two sub-traits sociability E1 and activity E2) and Honesty (L).

The meta-analysis of Trapmann et al. [37] investigates the impact of the Big Five personality factors (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism) 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. Significant correlation between personality traits (Extroversion, Neuroticism and Conscientiousness) and examination grades of 247 British university students, explaining around 15% of the variance was found in the study of Chamorro-Premuzic and Furnham [4].

The learning environment is another factor influencing academic performance, especially in blended scenarios which involve technology in education. Synchronous environments such as videoconferences are advantageous for social learners who prefer and benefit from the interaction with their peers. On the other hand, asynchronous environment that enables individuals to learn at their own pace, schedule and autonomy, is preferred for solitary learners [27].

The impact of the media presentation on the acceptance of the e-learning technology is given in [18,28]. Authors have explored three different media types i.e. text, streamed audio and streamed video. The perceived usefulness and the user's attitude were used to predict the intention to use the system. The effect of the media on the student's satisfaction and engagement is given in [36,41]. The authors conclude that the asynchronous rich media presentations increase the student's satisfaction with the on-line courses.

In the study of Martínez et al. [30], person's personality is estimated using Big Five personality test and the results of the five personality traits are used as inputs in an ANFIS model. The output from the ANFIS is the role in the software engineering development team. The system is used to recommend the most suitable roles for novel persons in software engineering teams.

The impact of the technical characteristics of the underlying technology on the overall user satisfaction with the delivered service, and the adaptation of the service performance on variable network conditions is explored in [22,23]. The authors propose an ANFIS based neuro-fuzzy model using a combination of application and physical layer parameters to predict the delivered video quality to the users. In the study authors use ANFIS to train three neural networks for three distinct content types, to predict the video quality in terms of MOS. The accuracy of the model was validated by the correlation coefficient and RMSE. The results showed that network level parameters bandwidth and packet error rate have a much bigger impact on video quality compared to application level parameters such as frame rate and video send bitrate.

3. ANFIS theoretical framework

Adaptive Neuro Fuzzy Inference System (ANFIS) is a hybrid neuro-fuzzy system described by Jang [19]. ANFIS possesses some unique properties integrating the advantages of neural networks and fuzzy logic techniques for human behavior representation. Fuzzy inference systems provide a strong mechanism for knowledge representation when expert knowledge is available but do not possess capabilities for automated learning. Neural networks on the other hand have powerful mechanism of learning from sample data when expert knowledge is limited, but do not possess knowledge representation capability. ANFIS overcomes the limitations of both techniques, offering particularly strong system identification technique when the relationship between input and output is not trivial. This means that ANFIS is able to build a fuzzy rule base and tune the parameters of the membership functions from a given set of input/output data.

ANFIS is a five layered structure, having different nodes in each layer connected with the nodes from the previous level receiving input signals coming from the output signals from the previous level, as given in the Fig. 1.

The rule base consists of Takagi-Sugeno type rules. A typical rule with two input and one output variables in this model is:

$$\text{Rule i}: \quad \text{if } x_1 \text{ is } A_i \text{ and } x_2 \text{ is } B_i \text{ then } f_i = p_i x_1 + q_i x_2 + r_i$$

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). The complexity of the rule base depends on the number of input variables and the number of values in term sets.

4. Research design of the ANFIS model for QoE prediction

The ANFIS model for QoE evaluation was developed in the following steps:

Step 1: Definition of input/output variables and collection of data sets

Step 2: Initialization of the system structure and training the ANFIS

Step 3: Evaluation of the system performance

The Matlab Fuzzy Logic Toolbox is used for definition, training and evaluation of the system.

4.1. Definition of input/output variables and collection of data sets

Following the literature review we defined a set of seven possible input variables, attempting to incorporate both objective and subjective aspects influencing student's perception in technology aided educational process. Objective variables are defined regarding the NQoS parameters: Packet Loss (PL), Latency (Lat) and Jitter (Jit). The values for objective variables were collected from the network log readings obtained from the 96 videoconference and video streaming sessions that were held during this case study. The least favorable value from the transmitted (Tx) and received (Rx) streams during each session was used during the calculations, since the highest value determines the variance in networking performance.

Subjective variables regarding the personality traits Neuroticism (N1) and Extroversion (E3) are defined according to HANES methodology [1]. The values for N1 and E3 were obtained from the scores of HANES personality tests completed by the 142 students involved in this study.

The HANES methodology evaluates the results from the HANES-1 and HANES-2 on [1–9] scale and classifies the degree of neuroticism and extroversion as given in Table 3.

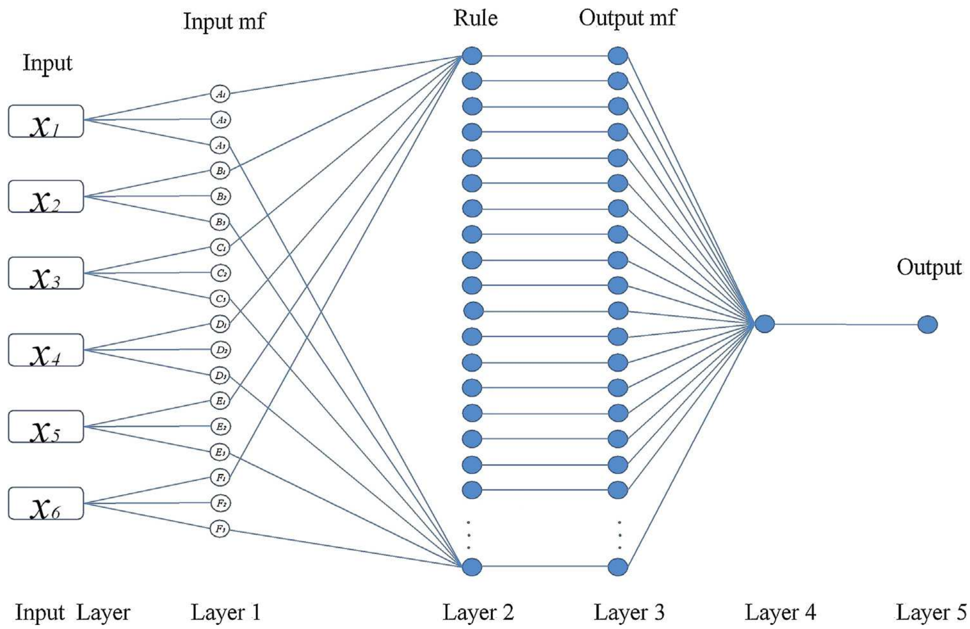


Fig. 1. The graphical representation of six input ANFIS system.

Table 3
The classification of neuroticism and extroversion in HANES methodology.

N1, E3	Extremely below average	Below average	Average	Above average	Extremely above average
Score	1	2, 3	4, 5, 6	7, 8	9

Learning style variable (VARK) is defined according to VARK methodology [11]. VARK methodology recognizes 23 learning style profiles as given in Table 4.

The model outputs a single variable (QoE). The values for the QoE variable were obtained through age-appropriate questionnaires which were designed and interpreted following the methodology given in [29]. In like manner, the students were able to grade QoE on a five-point Likert scale [26] after each learning session, while providing feedback on questions which reflected students' satisfaction regarding the learning environment and their beliefs for increased efficiency and productivity. The mean value of the feedback scores was used as overall perceived QoE.

The complete list of I/O variables is given in Table 5.

The complete I/O data set of 1704 vectors was obtained from the evaluation of 142 students, engaged in 6 games on classes with 2 media types (VC and VS). The complete data set was randomly divided into training data set of 1000 data rows and the checking data set of 704 data rows.

Table 4
Learning style preferences according to VARK methodology.

Learning style preference	Profile	Value
V	Visual (very strong, strong, mild)	1, 2, 3
A	Aural (very strong, strong, mild)	4, 5, 6
R	Read/write (very strong, strong, mild)	7, 8, 9
K	Kinesthetic (very strong, strong, mild)	10, 11, 12
Bimodal	VA, VR, VK, AR, AK, RK	13, 14, 15, 16, 17, 18
Trimodal	VAR, VAK, ARK, VRK	19, 20, 21, 22
Multimodal	VARK	23

4.2. Initialization of the system structure and training the ANFIS

The FIS structure to be used in ANFIS learning cycles can be initialized using grid partitioning or subtractive clustering algorithm. The grid partitioning algorithm generates rule base by enumerating all possible combinations of membership functions of all inputs, leading to exponential growth of the rule base referred as "curse of dimensionality". Subtractive clustering is a one-pass algorithm for estimating the number of clusters and the cluster centers in a dataset. The subtractive clustering algorithm efficiently generates significantly smaller rule base depending on a predefined cluster radius.

Having the "curse of dimensionality" limitation when more than 5 variables are used for grid partitioning of the initial FIS structure in Matlab, we had to reduce the input variable set to the four most influential inputs to the desired output. The heuristic method for input selection proposed by Jang in [20] reduces the input variable set by constructing several ANFIS models with smaller number of input variables from the initial set, and estimates the training Relative Mean Square Error (RMSE) in one training epoch for each evaluated model. The model that produces smallest RMSE in one epoch is assumed to outperform the other models after further training as well.

We used exhsrch command of Matlab to evaluate 35 ANFIS models from the initial 7 variables. The model having N1, E3, VARK and Jit variables produced the smallest RMSE in one training epoch. Therefore it is reasonable to assume that these input variables are most influential to the desired output.

We constructed three ANFIS systems: ANFIS-s7 with seven input variables (N1, E3, VARK, Jit, PL, Lat, CT) using subtractive clustering; ANFIS-g4 and ANFIS-s4 with four input variables (N1, E3, VARK, Jit) using grid partitioning and subtractive clustering respectively.

Table 5
List of ANFIS I/O variables.

Variable name	Description	Type	Source	Range of values
PL	Packet loss (Tx/Rx)	Objective	Network log	[0–8] %
Lat	Latency (Tx/Rx)	Objective	Network log	[0–1213] ms
Jit	Jitter (Tx/Rx)	Objective	Network log	[0–240] ms
N1	Neuroticism	Subjective	HANES personality test	[1–9]
E3	Extroversion	Subjective	HANES personality test	[1–9]
VARK	Learning style	Subjective	VARK questionnaire	[1–23]
CT	Content type	Objective	constant values: 1 – logical 2 – visual 3 – social	[1–3]
QoE	Quality of Experience	Output	Questionnaire	[1–5]

Table 6
The comparison of ANFIS-s and ANFIS-g structure.

	ANFIS-s7	ANFIS-g4	ANFIS-s4
No. nodes	426	305	197
No. linear parameters	208	675	95
No. nonlinear parameters	364	42	152
Total no. parameters	572	717	247
No. training data pairs	1000	1000	1000
No. checking data pairs	704	704	704
No. fuzzy rules	26	135	19
No. training epochs	50	50	50

ANFIS-s7 and ANFIS-s4 are constructed with 0.42 range of influence of data cluster centers. ANFIS-g4 is constructed using three triangular membership functions for N1, E3 and Jit variables and five triangular membership functions for VARK variable.

The initial structures of ANFIS systems are given in Table 6.

The initial systems are trained using the anfis command in 50 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. During the training process the checking error slightly decreases in each epoch until around epoch 50 when it slightly increases (Fig. 2). This indicates that 50 epochs are optimal choice for our model training because further increase of the training epochs may produce model over fit.

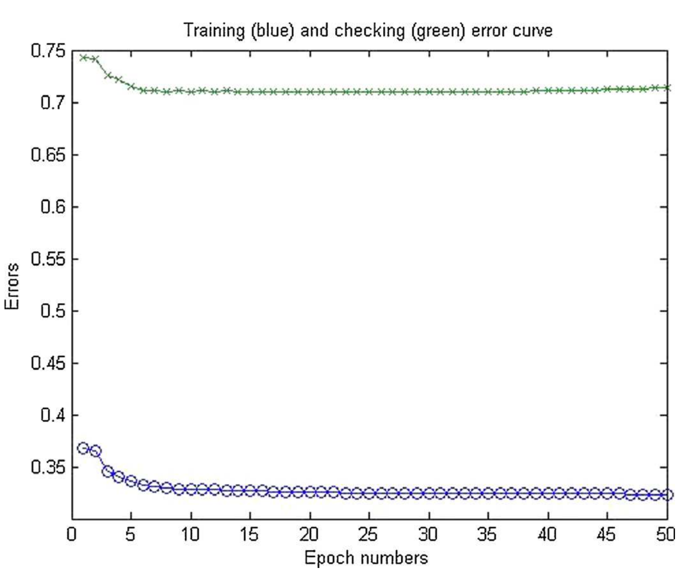


Fig. 2. Comparison of training and checking errors from ANFIS-g4.

4.3. Evaluation of the system performance

Model validation evaluates how well the model predicts the output values of a data set on which the FIS was not trained. This type of validation is appropriate when the training dataset is fully representative of the features of the data that the trained FIS is modeling. Model validation may be performed using a separate checking data set to control the potential of the model over fitting the data. Over fitting occurs when the obtained model describes random error or noise instead of the underlying relationship. In our model the dataset of observations is randomly separated into training dataset and checking dataset for model validation. The size of the dataset of observations is relatively large to the number of parameters of the system to ensure that the training dataset is representative of the resulting model, and the checking dataset is distinct from the training data to ensure that the validation process is not trivial.

5. Results and discussion

The performance of the ANFIS-s7, ANFIS-g4 and ANFIS-s4 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:

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

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

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

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

The comparison of the results is given in Table 7.

Table 7
The comparison of RMSE and MAPE of ANFIS-s7, ANFIS-g4 and ANFIS-s4.

	ANFIS-s7	ANFIS-g4	ANFIS-s4
Training RMSE	0.6079	0.3236	0.5264
Checking RMSE	1.7398	0.7094	0.7381
Linear regression RMSE (against checking data)	1.3278	0.8906	0.8906
Training MAPE	12.2483	4.6263	9.1210
Checking MAPE	102.3401	16.5258	12.3196
Training R^2	0.4927	0.8244	0.5353

The results show that ANFIS-g4 and ANFIS-s4 with 4 input variables outperform ANFIS-s7 with 7 input variables. This result supports the assertion that appropriate input selection is essential for proper system modeling. Excessive number of inputs can impair the model and increase complexity of the system. Three of the four most influential input variables to the student perception expressed as QoE are of subjective nature, supporting the literature findings on the influence of personality traits and learning style on the student satisfaction and academic performance. Our study shows that subjective factors have greater impact on the perceived QoE, than the objectively measured network parameters. ANFIS-g4 and ANFIS-s4 produce lower RMSE compared to the linear regression RMSE against checking data, which clearly indicates that ANFIS models with four input variables outperform the linear regression model.

ANFIS-g4 with grid partitioning produces lowest training and checking RMSE, and lowest training MAPE. ANFIS-g4 also produces the highest R^2 value, having the quadruple of variables (N1, E3, VARK, Jit) explaining approximately 82% of the variance in QoE on the training dataset, thus contributing the goodness of fit of the ANFIS-g4 model. These results lead to conclusion that ANFIS-g4 gives the best QoE predicting performance among the assessed systems in this study. The R^2 value of 82% produced from ANFIS-g4 is comparable to the R^2 findings (up to 87%) reported in comparative studies [5,23].

The error curves and comparison of actual and predicted output values from ANFIS-g4 are given in Figs. 2 and 3, respectively. Fig. 2 shows that after 15 epochs of training, error curves remain stable until around epoch 45 when the checking error curve starts to rise, signalizing model over fit. Therefore, the model produces best results with approximately 40 epochs of training.

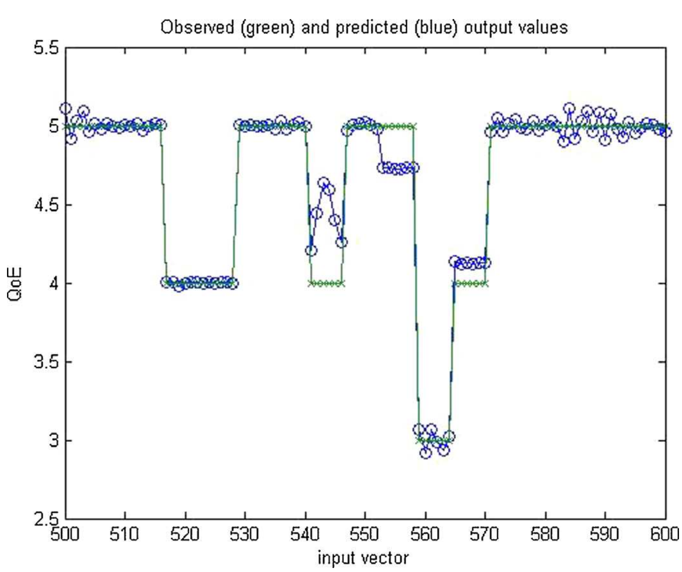


Fig. 3. Comparison of actual and predicted output values from ANFIS-g4.

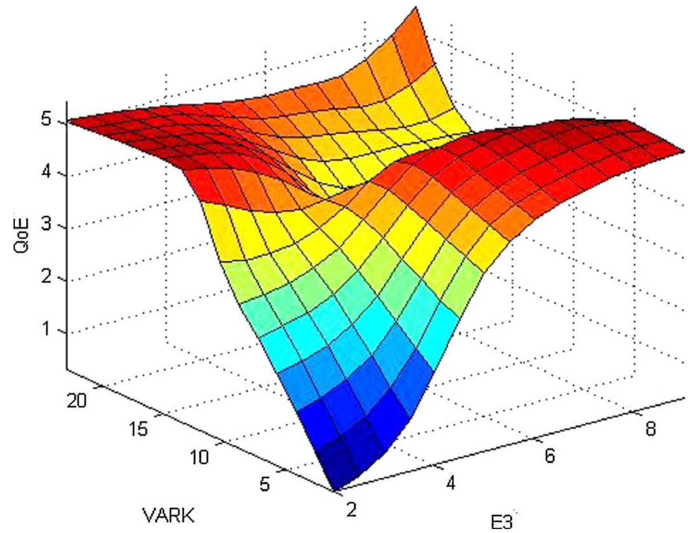


Fig. 4. Effect of VARK and E3 on QoE.

The effects of the input parameters on the QoE are depicted by the ANFIS-g4 surfaces given on the Figs. 4–6 respectively. The surfaces are obtained by varying two parameters and keeping the other two fixed. The surface on Fig. 4 shows that students with multimodal learning style and very strong extrovert personality trait produce the highest QoE values. Surface on Fig. 5 shows that lower values for neuroticism combined with average and above extroversion values results in highest QoE perception. Fig. 6 shows the negative effect of the jitter on the perceived QoE.

6. Comparison with other prediction models

To further investigate the relationship between input variables used in ANFIS model and perceived QoE, we performed linear regression LR-7 on the complete set of 1704 input vectors, as given in Table 8.

The results of t-statistics and their associated 2-tailed p-values used to estimate the effect of the independent variables (predictors) on the resulting QoE, are given in Table 9. The null hypothesis states that given coefficient is equal to zero at alpha level of 0.05, which means that the corresponding variable has no effect on the model.

The p-values for a, b and c coefficients (N1, E3 and VARK variables) are lower than the alpha value, which leads to conclusion

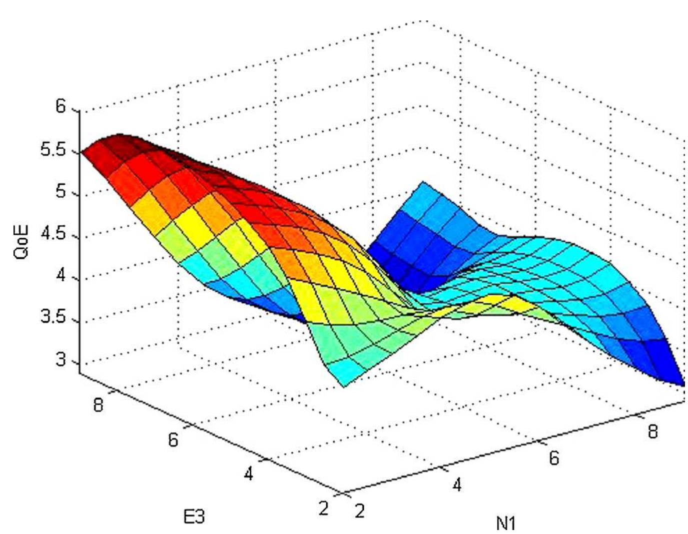


Fig. 5. Effect of N1 and E3 on QoE.

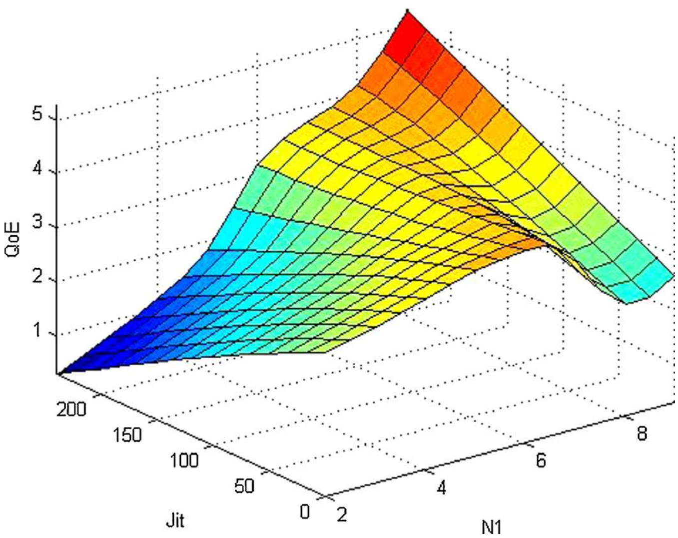


Fig. 6. Effect of N1and Jit on QoE.

Table 8
The linear regression model LR-7.

	LR-7
Independent variables	N1, E3, VARK, CT, PL, Lat, Jit
Dependent variable	QoE
Regression equation	QoE = a*N1 + b*E3 + c*VARK + d*CT + e*PL + f*Lat + g*Jit + h
F-value (ANOVA)	10.819
p-value (ANOVA)	0.000
RMSE	0.7977
R^2	0.043

that they are significantly different from zero. The p-value for the g coefficient (Jit variable) is greater than the alpha level, meaning that it is not significantly different than zero. The LR-7 model indicates that from the set of seven independent variables, the most influential on the perceived QoE are N1, E3 and VARK variables. This is compliant with the choice of subjective variables in construction of the ANFIS-s4 and ANFIS-g4 models. Besides subjective variables, ANFIS-g4 and ANFIS-s4 models include the Jit variable as influential to the perceived QoE. Having the results in previous section confirming that ANFIS-g4 and ANFIS-s4 produce lower RMSE than the corresponding linear regression RMSE, we conclude that ANFIS is appropriate modeling technique for QoE prediction in education.

The results of our study are comparable with the results given in [21,23] in terms of RMSE and R^2. The framework given in [39] proposes QoE prediction based on construction of a QoE space with arbitrary k-dimensions representing the parameters that potentially affect video quality in video streams. However these studies are mostly concerning the QoS parameters affecting video

Table 9
The t-statistics on LR-7 coefficients.

Variable	LR-7			
	Reg. coefficient	Coefficient value	t-value	p-value
(Constant)	h	4.291	33.773	.000
N1	a	−0.043	−3.608	.000
E3	b	0.028	2.678	.007
VARK	c	0.017	5.939	.000
CT	d	−0.002	−0.098	.922
PL	e	0.000	−0.676	.499
Lat	f	0.000	−1.799	.072
Jit	g	0.002	1.412	.158

quality. Our study makes an attempt to give a broader view on QoE assessment in technology aided education by examining the subjective factors concerning personality and learning style altogether with the objective network factors. Our results are compatible with the findings in the sociological studies regarding the influence of personality and learning style on student's satisfaction and academic success.

7. Future work

The case study given in this paper presents the results of the proposed ANFIS system for QoE prediction based on the experiences of the primary school students participating in the study. To further explore the capability and efficiency of the proposed ANFIS system, we performed an additional QoE study including 95 students from the Faculty of Computer Science and Engineering that enrolled "Search Engines" and "Designing Dynamic Web Sites" distance learning courses, set up on the faculty's Moodle interactive e-learning platform. In the later study we introduced 9 input variables to the ANFIS system. Besides the objective NQoS input variables (PL, Lat, Jit) and the subjective Learning Style (VARK) variable, we introduced the "Big Five" personality traits (Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness) as subjective input variables, assessed using the revised NEO personality inventory (NEO–PI-R) [42] that was completed by each student participating in the study. The ANFIS system in the later study with 9 input variables produced compliant values (training RMSE = 0.6949, checking RMSE = 1.3883, training MAPE = 13.8198, checking MAPE = 40.5256) with the corresponding values reported in the present study. The preliminary results reveal that the network jitter (Jit), as well as the Extraversion, Openness and Conscientiousness personality traits are the most influential factors on the student's perceived QoE. However, the study yet to be completed aims to deeply explore the other factors such as the influence of the quality of instructional material and the instructor's teaching style on the QoE. The path analysis techniques will be employed to explore the correlations among the input variables in the system, as well as the correlation between the QoE and academic performance.

8. Conclusion

This paper presented a neuro fuzzy model of Quality of Experience prediction for students in a blended learning environment that utilized technology enriched classrooms including videoconferences and video streaming lessons. We explored variety of factors influencing perceived QoE, aiming to construct a model that would incorporate both objective factors affected by the underlying technology and subjective factors affected by the student individual preferences and expectations. Our findings suggest that in a controlled network environment, the perceived QoE is mostly influenced by the factors of subjective nature determined by the person's personality traits and learning style. The influence of the underlying technology was mostly apparent through variations of the network jitter. While retaining the subjective perception as main QoE determinant, this model overcomes the low cost effectiveness of the MOS related models by offering a priori prediction of the student satisfaction with a given technology enriched educational setup. The ANFIS based QoE prediction produced better RMSE than the linear regression prediction model, and a satisfactory R^2 value (0.8244) for a social science research.

In our further work we will explore the correlation between the perceived QoE and the academic performance of the students involved in the study. The findings will be utilized to classify the students in few stereotype groups, in order to provide appropriate learning environment to each group that would produce best results regarding the student satisfaction and academic performance.

Having the initial encouraging results from the ANFIS based QoE prediction model, further application of the model might be extended to other areas, especially ones that use videoconferencing and streaming as underlying technology. In business this model can be customized to provide the most suitable training platform of the employees scattered on different locations. Receiving instructions for online services or products might be another possible area of application. The system can be retrained using a dataset collected from different network conditions and volunteers participating in an online survey to collect their personality traits as well as the experienced satisfaction with different setups, in order to obtain conclusions for the QoE of different profiles of users. Online rental services offering electronic content may also benefit from a system that would estimate the QoE of their users.

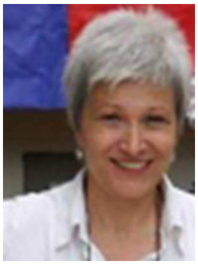
Acknowledgments

We would like to express gratitude to the work of teachers Tinka Bedzovska, Vesela Bogdanovik, Cvetanka Karovska, Maja Kitanoska, Nada Krsteva, Olivera Palifrova, Mica Miteva and Daniela Krstevska who practically implemented the ideas presented in this work.

References

[1] Ž. Bele-Potočnik, D. Hadžiselimović, M. Tušak, HANES-Skala neuriticizma i ekstroverzije za decu i omladinu-Priručnik, Zavod za produktivnost dela, Ljubljana, 1977.
[2] V.V. Busato, F.J. Prins, J.J. Elshout, C. Hamaker, Intellectual ability, learning style, personality, achievement motivation and academic success of psychology students in higher education, Personal. Individ. Differ. 29 (6) (2000) 1057–1068.
[3] P. Calyam, M. Haffner, E. Ekici, C.G. Lee, Measuring Interaction QoE in Internet Videoconferencing in Real-Time Mobile Multimedia Services, Springer, Berlin, Heidelberg, 2007, pp. 14–25.
[4] T. Chamorro-Premuzic, A. Furnham, Personality traits and academic examination performance, Eur. J. Personal. 17 (3) (2003) 237–250.
[5] T. Chamorro-Premuzic, A. Furnham, Personality, intelligence and approaches to learning as predictors of academic performance, Personal. Individ. Differ. 44 (7) (2008) 1596–1603.
[6] H.P. Chow, Exploring the predictors of educational experience and academic performance among university students in Regina, Alberta J. Educ. Res. 49 (1) (2003) 101–105.
[7] A. Duff, E. Boyle, K. Dunleavy, J. Ferguson, The relationship between personality, approach to learning and academic performance, Personal. Individ. Differ. 36 (8) (2004) 1907–1920.
[8] S. Egger, M. Ries, P. Reichl, Quality-of-experience beyond MOS: experiences with a holistic user test methodology for interactive video services, in: Proc. of 21st ITC Specialist Seminar, Miyazaki, Japan, 2010 March.
[9] S.B. Eom, J.B. Arbaugh (Eds.), Student Satisfaction and Learning Outcomes in e-Learning: An Introduction to Empirical Research, Information Science Reference, 2011.
[10] H.J. Eysenck, Dimensions of Personality, Transaction Books, 1947.
[11] N. Fleming, Teaching and Learning Styles – VARK Strategies, Microfilm, Ltd., Christchurch, New Zealand, 2006, pp. 2006.
[12] A. Furnham, C.J. Jackson, T. Miller, Personality, learning style and work performance, Personal. Individ. Differ. 27 (6) (1999) 1113–1122.
[13] E. Giles, S. Pitre, S. Womack, Multiple intelligences and learning styles, in: M. Orey (Ed.), Emerging Perspectives on Learning, Teaching and Technology, 2003.
[14] E. Gurpinar, M.K. Alimoglu, S. Mamakli, M. Aktekin, Can learning style predict student satisfaction with different instruction methods and academic achievement in medical education? Adv. Physiol. Educ. 34 (4) (2010) 192–196.
[15] C. Hatting, End-to-End QoS Network Design, Cisco Press, 2005.
[16] International Telecommunication Union, ITU-T IPTV Focus Group Proceedings, 2008.
[17] A.F. Grasha, Teaching With Style: A Practical Guide to Enhancing Learning by Understanding Teaching and Learning Styles, Alliance Publishers, 1996.
[18] P.A. Havice, K.W. Foxx, T.T. Davis, W.L. Havice, The impact of rich media presentations on a distributed learning environment, Q. Rev. Distance Educ. 11 (1) (2010) 53.
[19] J.S.R.C. Jang, T. Sun, Neuro-fuzzy modeling and control, in: Proceedings of the IEEE Issue Date: March 1995, 1995, pp. 378–406.
[20] J.S. Jang, Input selection for ANFIS learning, in: Proceedings of the Fifth IEEE International Conference on Fuzzy Systems, FUZZ-IEEE'96 (vol. 2), 1996 September, pp. 1493–1499.
[21] A. Khan, L. Sun, E. Ifeachor, An ANFIS-based hybrid video quality prediction model for video streaming over wireless networks, in: Proc. of 2nd IEEE Conference and Exhibition on Next Generation Mobile Application, Services and Technologies, 2008.
[22] A. Khan, L. Sun, E. Jammeh, E. Ifeachor, Content classification-based and QoE-driven video send bitrate adaptation scheme, in: Mobimedia '09 Proceedings of the 5th International ICST Mobile Multimedia Communications Conference ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), ICST, Brussels, Belgium, 2009.
[23] A. Khan, L. Sun, J.-O. Fajardoi, F. Liberal, E. Ifeachor, An ANFIS-based hybrid quality prediction model for H.264 video over UMTS networks, in: Proc of IEEE CQR, 8–10 June 2010, Vancouver, Canada, 2010.
[24] J. Klaue, B. Rathke, A. Wolisz, EvalVid – a framework for video transmission and quality evaluation, in: Proc. of the 13th International Conference on Modelling Techniques and Tools for Computer Performance Evaluation, 2003.
[25] F. Kuipers, R. Kooij, D. De Vleeschauwer, K. Brunnström, Techniques for measuring quality of experience, in wired/wireless Internet communications, Lecture Notes Comput. Sci. 6074 (2010) 216–227.
[26] R. Likert, A technique for the measurement of attitudes, in: Archives of Psychology, Columbia University Press, New York, 1931.
[27] Y. Liu, D. Ginther, Cognitive styles and distance education, Online J. Distance Learn. Adm. 2 (3) (1999).
[28] S.H. Liu, H.L. Liao, J.A. Pratt, Impact of media richness and flow on e-learning technology acceptance, Comput. Educ. 52 (3) (2009) 599–607.
[29] T. Malinovski, M. Vasileva, V. Trajkovik, Integrating Computer Games in Primary Education for Increased Students' QoE, in: ICT Innovations 2013, Springer International Publishing, 2014, pp. 35–44.
[30] L.G. Martínez, A. Rodríguez-Díaz, G. Licea, J.R. Castro, Big five patterns for software engineering roles using an ANFIS learning approach with RAMSET, in: Advances in Soft Computing, Springer, Berlin, Heidelberg, 2010, pp. 428–439.
[31] K. Mintauckis, Empirical Studies of Quality of Experience (QoE): A Systematic Literature Survey, 2010.
[32] S.T. Mustafa, D. Chiang, Dimensions of quality in higher education: how academic performance affects university students' teacher evaluations, J. Am. Acad. Bus. 8 (1) (2006) 294–303.
[33] A.S. Patrick, J. Singer, B. Corrie, S. Noel, K. El Khatib, B. Emond, S. Marsh, A QoE sensitive architecture for advanced collaborative environments, in: Quality of Service in Heterogeneous Wired/Wireless Networks, 2004. QSHINE 2004, First International Conference on IEEE, 2004 October, pp. 319–322.
[34] O. Samdal, B. Wold, M. Bronis, Relationship between students' perceptions of school environment, their satisfaction with school and perceived academic achievement: an international study, School Eff. School Improv. 10 (3) (1999) 296–320.
[35] M. Siller, J. Woods, Improving quality of experience for multimedia services by QoS arbitration on a QoE framework, in: Proc. of the 13th Packed Video Workshop 2003, 2003 April.
[36] P.-C. Sun, R.J. Tsai, G. Finger, Y.-Y. Chen, D. Yeh, What drives a successful e-learning? An empirical investigation of the critical factors influencing learner satisfaction, J. Comput. Educ. 50 (May (4)) (2008) 1183–1202, 2008.
[37] S. Trapmann, B. Hell, J.O.W. Hirn, H. Schuler, Meta-analysis of the relationship between the big five and academic success at university, Z. Psychol. 215 (2) (2007) 132–151.
[38] T. Vasileva-Stojanovska, V. Trajkovik, Modeling a Quality of Experience aware distance educational system, in: ICT Innovations 2013, Springer International Publishing, 2014, pp. 45–55.
[39] M. Venkataraman, M. Chatterjee, S. Chattopadhyay, Evaluating quality of experience for streaming video in real time, in: Global Telecommunications Conference, 2009. GLOBECOM 2009 IEEE, IEEE, 2009 November, pp. 1–6.
[40] W. Wu, A. Arefin, R. Rivas, K. Nahrstedt, R. Sheppard, Z. Yang, Quality of experience in distributed interactive multimedia environments: toward a theoretical framework, in: Proceedings of the 17th ACM International Conference on Multimedia, ACM, 2009 October, pp. 481–490.
[41] P.A. Havice, T.T. Davis, K.W. Foxx, W.L. Havice, The impact of rich media presentations on a distributed learning environment, Q. Rev. Distance Educ. 11 (1) (2010) 53–58.
[42] P.T. Costa, R.R. McCrae, The revised neo personality inventory (neo-pi-r) SAGE Handbook of Personality Theory and Assessment, vol. 2, 2008, pp. 179–198.

Tatjana Vasileva-Stojanovska received her Master Degree in Computer Science at the Faculty of Electrical Engineering and Information Technologies, Ss. Cyril and Methodius University – Skopje, Macedonia in 2000. Her main research interests include distance education, intelligent agent technology, fuzzy logic, and neuro-fuzzy modeling. Her ongoing PhD thesis research is focused on Quality of Experience modeling in education. Works at the National Bank of the Republic of Macedonia.



Marina Vasileva completed her Master Degree at the Pedagogical Faculty, Ss. Cyril and Methodius University – Skopje, Macedonia in 2011. She is a PhD candidate at the Faculty of Computer Science and Engineering at the Ss. Cyril and Methodius University – Skopje, Macedonia, with research activities which focus on didactic aspects for the development of educational contents which utilize ICT. Works at Primary School "Ss. Cyril and Methodius" in Skopje and also holds the position as IT teacher for students at the Ss. Cyril and Methodius University – Skopje, Macedonia.

Toni Malinovski has completed his Master Degree in Computer Science at the Faculty of Electrical Engineering and Information Technologies, Ss. Cyril and Methodius University – Skopje, Macedonia in 1998. He is a PhD candidate at the same university with ongoing research in distance education, rich communication media, QoS/QoE, videoconferencing and distributed systems. Works at National Bank of the Republic of Macedonia and holds the position as IT senior consultant.

Vladimir Trajkovik received his PhD Degree at the Ss. Cyril and Methodius University – Skopje, Macedonia in 2003. Currently he is a professor at the Faculty of Computer Science and Engineering at the same university. His research interests include: information systems analyses and design, distributed computer systems, distance educational systems, multi-agent systems, ICT-based collaboration systems and mobile services. He has over 100 publications in various international conferences and international journals.