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THE PERCEPTION OF E-LEARNING QUALITY IN HIGHER EDUCATION: SEM-ANN APPROACH

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Abstract

The pandemic resulted in lockdown measures worldwide, which forced humanity to seek online alternatives to almost every human activity, including the education system. This research aims to develop a new integrated model to determine the predictors of the quality of E-learning during the pandemic disruption. This paper provides the development of the traditional approach based on Structural Equation Modelling (SEM) into the prediction method based on the Artificial Neural Network (ANN). This research was conducted on a sample comprising 1,254 students of the University of Belgrade. The results show that Authority initiative had the most important influence and significance in predicting the perception of the Quality of E-learning during the pandemic. At the same time, the Information Security predictor had the most negligible impact. The findings contribute to the raising the academic community and policy-makers awareness to the necessity of dealing with quality in E-education to a greater extent, especially in emergencies such as pandemics. The suggested combination of constructs that predict the Quality of E-learning has never been analysed in previous research by applying SEM-ANN methodology, which represents the additional contribution of this study.

Key words: quality, E-learning, pandemic, higher education, SEM-ANN.

ПЕРЦЕПЦИЈА КВАЛИТЕТА Е-УЧЕЊА У ВИСОКОМ ОБРАЗОВАЊУ: SEM-ANN ПРИСТУП

Апстракт

Пандемија је изазвала мере закључавања широм света које су приморале човечанство да прибегне онлајн алтернативама у скоро свакој људској активности, што је био случај и са образовним системом. Ово истраживање има за циљ да развије нови интегрисани модел за одређивање предиктора квалитета е-учења током COVID-19 пандемије. Овај рад обезбеђује развој традиционалног присту-

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па заснованог на моделирању структурних једначина (SEM) у методу предвиђања заснoвану на вештачкој неуронској мрежи (ANN). У овом истраживању је учествовало 1.254 студената Универзитета у Београду. Резултати показују да иницијатива управе факултета има најважнији утицај и значај у предвиђању перцепције квалитета електронског учења током пандемије. Истовремено, предиктор „сигурност информација" има најмање значајан утицај. Резултати доприносе подизању свести академске заједнице и твораца политика о потреби да се више баве квалитетом е-образовања, посебно у ванредним ситуацијама као што је пандемија. Предложена комбинација конструката који предвиђају квалитет е-учења никада није анализирана у претходним истраживањима применом SEM-ANN методологије, што представља додатни допринос ове студије.

Кључне речи: квалитет, Е-учење, пандемија, високо образовање, SEM-ANN.

INTRODUCTION

The COVID-19 pandemic disruption has resulted in social distancing and lockdown measures which forced people worldwide to use electronic services for learning, work, and leisure (Favale et al., 2020). Hence, information and communication technology has been used to maintain organisations' core business more than ever (Yallop & Aliasghar, 2020). Additionally, it has never been more necessary to set up supplemental E-learning so rapidly (Tretter et al., 2020). In Europe, many schools, faculties and universities diverted regular class meetings to online meetings (Randjelovic et al., 2022). Non-traditional learning and teaching forms became necessary, and the only way to maintain the teaching process' continuity (Stanković, 2020). In, those days, E-learning was becoming a mainstream teaching and communication tools (Das De et al., 2020). In the circumstances caused by the pandemic, education systems in many countries underwent changes in regular functioning. In early March 2020, all higher education institutions within the University of Belgrade temporarily stopped their work and switched to various E-learning platforms. The University of Belgrade also followed the government's proposed measures, and faculties within the same university had to undergo rapid changes. The faculties had the freedom to decide how to hold their planned classes, and which platforms and applications they would employ. Although distance and E-learning are not unknown at these faculties, a small number of them wanted to transfer traditional to virtual classes and obligations, which is corroborated by data that only several faculties have accredited distance study programmes. On the other hand, there is an area where E-learning is not an acceptable solution due to practical exercises such as experiments and activities within faculties of medicine, dentistry, pharmacy, sport, technology, etc. However, the COVID-19 pandemic left educational institutions no choice, and this necessary transformation could significantly affect students' satisfaction, and thus their expectations regarding the quality of E-learning.

This study aims to integrate different models to examine the perception of the quality of E-learning during the COVID-19 pandemic. Therefore, the objectives of this study are twofold. In order to address the existing literature gap concerning the pandemic's impact on education, a conceptual model was put forth. This model was then examined using Structural Equation Modeling (SEM) to fulfil the first aim of exploring the potential influence of *simplicity of using* and *authority-driven initiatives* on the *quality of E-learning* amid the coronavirus situation. Additionally, the impact of control variables *information security* and *accuracy* on the quality of E-learning was examined. The second aim is to develop a new model that predicts the perception of the quality of E-learning during the pandemic caused by COVID-19. For this purpose, SEM model dimensions serve as inputs in ANN modelling.

THEORETICAL BACKGROUND AND HYPOTHESES

E-learning is an "application of IT that is widely used in the educational sector" (Pour et al., 2019, p. 116). Before the coronavirus, E-learning was becoming more and more popular in high education due to various teaching and learning opportunities for educational institutions and students (Pham et al., 2019). E-learning is structurally different compared to conventional learning (Jung, 2010), but it mainly provides students with a personalised and flexible way to study and learn (Cidral et al., 2018). Students want to study, work, and learn whenever and wherever they want. Still, it is believed that E-courses are perceived as lower quality courses due to limited interaction, particularly in presentations, and lack of peer and teacher support (Uppal & Gulliver, 2017). On the flip side, virtual activities reduce education costs and provide flexible accessibility of education without being hindered by place and time (Larmuseau et al., 2019). Despite the popularity of the online learning environment, delivering a quality E-service should still be an important goal for universities to retain and attract students without losing their productivity. As Farid et al. (2018, p. 3) assert, "the future of E-learning depends on the quality of E-learning systems". Accordingly, the quality of E-learning is an indicator of success that is not easy to build and manage (Brosser & Vrabie, 2015). Agariya and Singh (2012) stated that E-learning quality is the gap between students' experience with the offered E-services and their expectations. Further, given the large number of stakeholders, their different ways of thinking, and the requirements that need to be taken into account, E-learning's quality is an extremely complex issue (Brosser & Vrabie, 2015). Guided by the definition of Martínez-Caro et al. (2014), E-learning quality can be defined as the degree to which educational authorities meet stakeholders' needs or expectations. Two angles of identifying the quality of E-learning have been observed in literature. These are the quality of the software or platform for the realisation of education, and the quality of the education process itself (Nikolić et al., 2018).

As stated above, it is important to emphasise the necessity to understand how to manage the quality of E-learning. Numerous studies have shown that quality is the most significant factor for E-learning systems (Misut & Pribilova, 2015). As discussed before, quality can be evaluated by many indications and attributes which may have various influences on quality, such as pedagogy, authority, institution, learning background, instructor, performance, simplicity, information security and accuracy, interaction, learner, admin, etc. (Nikolić et al., 2018). Similarly, various models and approaches for quality assurance in E-learning can be found in literature (Misut & Pribilova, 2015). Those authors believe that the quality policies of successful learning with the support of information technology are equal to those in the traditional approach. Finally, by embracing E-learning as a relatively new approach to education, it should be emphasised that well-composed elements will ensure success regardless of applied technology (methods) (Misut & Pribilova, 2015).

Authority Initiative

Students' perception of the professor as an authority influences the education system (Gil-Madrona et al., 2020). The big challenges of authorities (faculties, universities, or teachers) in the distance learning process are innovative and structural changes, and their support to students in becoming E-learners (Levinsen, 2007). The significance of computer literacy skills should first run from the institutional level (Cvetković et al., 2021; Biškupić et al., 2015). Although there are no national recommendations for quality in E-learning, universities should engage lecturers/professors who have adequate references to ensure E-learning quality (Delva et al., 2019). A competent authority is characterised by the creation of learning conditions where warmth, truth, loyalty, and faith in students' potential have precedence (Gil-Madrona et al., 2020), particularly during the pandemic period. Research within higher education institutions in South Korea showed that staff support is the most powerful influencer, which explained about 80% of the variance in the quality of E-learning (Jung, 2010). Biškupić et al. (2015) pointed out that students' motivation is closely correlated with professors' contribution to the E-class and using technology overall. Therefore, the role of authority in students' guidance is essential, and without authority initiative and support in the integration of ICTs in education, the quality of E-service is nigh impossible. Therefore, the following hypothesis is set: *H1 – authority initiative* had a positive impact on the *quality of E-learning* during the pandemic period.

Simplicity

Some research has shown that effort and time management are the most important and positive predictors of academic quality performance (Neroni et al., 2019). Student engagement is the force and effort students invest in their E-learning environment (Bond et al., 2020). It is formed by various fundamental and internal factors, including the combined interaction of relations, learning processes, and learning conditions (Bond et al., 2020). Additionally, the degree to which students believe that using digital tools would be free of any effort is defined as simplicity of use (Mohammadi, 2015). It also refers to the ease of use (Ameen et al., 2019), or expected effort (Milošević et al., 2015a).

Educators proficient in using digital tools can design engaging and interactive online courses, making the learning process more simple, effective and enjoyable for students (Basar et al., 2021). Authorities can encourage the creation of high-quality, organised, and easily navigable digital content for E-learning. When educational materials are well-structured and readily available, students can more effectively engage with the content, leading to better learning outcomes (Samat et al., 2020). Furthermore, students sense self-confidence when some established practices ensure a friendly environment and when professors deal with procedures to overcome disruptive situation issues (Gil-Madrona et al., 2020). Mahdizadeh et al. (2008) and Sørebø et al. (2009) acknowledge that the professors' behaviour, motivation, and willingness to use E-learning are important facilitators and initiators of the students' utilisation of E-learning. In other words, without top-down initiative in the context of E-learning, the down-top reaction cannot be expected. Hence, the following hypothesis was formulated: *H2 – authority initiative* positively affected the *simplicity of use* in the E-learning process during the pandemic period.

Previous investigation has proved that perceived ease of use positively impacts the students' tendency to accept modern technology and has an important influence on perceived usefulness (Sabah, 2016). If learning applications and platforms are essentially easy to use, students will be more enthusiastic about examining their characteristics and permanently intending to use them (Hamid et al., 2016). According to Milošević et al. (2015b), simplicity of use can improve communication with students and professors, expand discussion, simplify post information about lectures and exams, and other university activities, thus improving the quality of the educational process. Accordingly, the next hypothesis is: *H3 – simplicity of use* in E-learning positively influenced the *quality of the E-learning* process during the pandemic period.

Information Accuracy and Security

The backbone of each E-learning process is information (Farid et al., 2018). One of the most important challenges students face in virtual education is the reliability and accuracy of released or published information (Dehghani et al., 2019). Accuracy of information exchange is a very significant quality dimension to raise students' understanding within the E-learning environment (Alla & Faryadi, 2013). In this context, the accuracy of information includes all information received from the authorities (professors and faculties), such as e-class schedules, deadlines, teaching material, assignments, or grades. Seddon and Kiew (1994) found a positive relationship between user satisfaction and information quality, and the accuracy of information is seen as one of the information quality constructs. During information sharing on learning platforms, students want to ensure that only those to whom the information is intended can see it (Siemens et al., 2017). It is not only a matter of personal information (name, surname, and grades) but also a matter of the students' personal views, opinions, and assignments. According to ISO 27000:2018, information security is defined as "preservation of confidentiality integrity and availability of information". Jerman-Blažić and Klobučar (2004) highlight that private risk may take different concerns in the online environment than those found in its physical counterpart, especially if professors use non-university-based learning platforms that the university/faculty cannot operate. According to the theory of communication, based on the IS success model, E-learning's quality also encompasses the accuracy, security, and efficiency of the information system (Lee & Lee, 2008). Hence, it is assumed that: *H4* – students who value the *accuracy of information* more valued the *quality of E-learning* in the pandemic period equally; and *H5* – students who value *information security* more valued the *quality of E-learning* in the pandemic period equally.

According to the developed hypotheses, the conceptual model is illustrated in Figure 1.

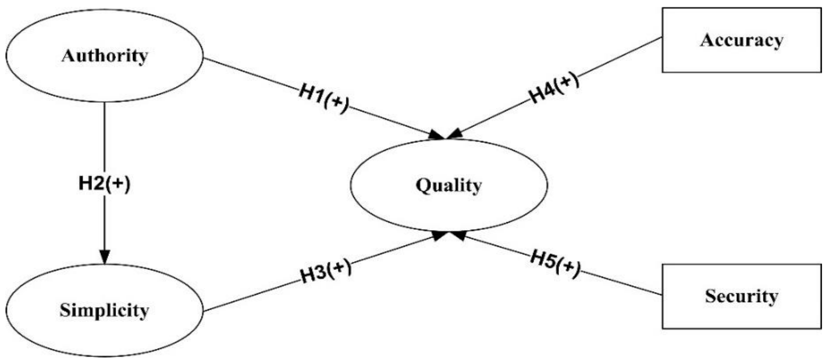

Figure 1. The Conceptual Model

RESEARCH METHODOLOGY

In this research, a two-step multi-analytical approach is employed to investigate if *authority initiative* and *simplicity of using* impact the *quality of E-learning* and predict the perception of the quality of E-learning during the pandemic period caused by COVID-19. According to previous research (Sharma, 2017; Asadi et al., 2019; Sohaib et al., 2020), this approach includes integrating SEM and ANN analyses (Zabukovsek et al., 2018). The first step of research is related to SEM, which contains two parts: a measurement model for validation of theory and modelling relationships among variables, and a structural model for testing three hypotheses. For the other two hypotheses, an analysis of variance (ANOVA) was additionally employed. In the second step, all SEM model significant variables served as input parameters for the ANN model. ANN is utilised to accurately predict significant factors for the perception of the quality of E-learning during the pandemic period. Although SEM methodology has been employed to test and verify hypothetical relationships, there is little research about its integration into other artificial intelligence algorithms (Xu et al., 2019). Moreover, there is less research that applies this integrated methodology in the field of the quality of E-learning. Thus, the literature gap is overcome. Because of its 'Black Box' operations, ANN does not provide testing of statistical hypotheses for their input variables, but it has some advantages compared with SEM and multiple regression analysis. For solving the proposed research problem, the ANN method can disclose both linear and non-linear relationships (Xu et al., 2019), enabling the prediction of the perception of the quality of E-learning during the pandemic period.

Sampling and Data Collection

To practically explore the extent to which the students of the University of Belgrade apply E-learning systems and which factors influenced the quality of E-learning during the pandemic period, a quantitative research method was used. For research purposes during a state of emergency, the authors modified and adapted the initial questionnaire based on previous studies, shown in the Appendix (Ahmad & Love, 2013; Milošević et al., 2015a). In the authors' opinion, the selected constructs – *authority initiatives*, *simplicity*, *security* and *accuracy* in E-learning are vital for maintaining and enhancing the quality of education provided in online environments. Through resource allocation, standardisation, accessibility, professional development, quality assurance, and innovation, educational authorities can foster an environment that supports effective and meaningful learning experiences for students, regardless of their location or circumstances. Furthermore, simplicity in E-learning is a key factor in determining the success of E-learning initiatives. By prioritising user-friendly design and implementation, educational institutions can enhance the overall quality of E-learning, create positive learning experiences, and foster a more inclusive and effective learning environment for all students. Regarding security, it is seen as an appropriate element for the quality of E-learning because investing in robust security measures demonstrates a commitment to the safety and well-being of students and educators, contributing to a successful and effective E-learning experience. Also, accuracy in E-learning is a crucial element that underpins the quality of the entire learning experience because it affects the learners' trust, engagement, outcomes, and ability to apply knowledge effectively.

The data was gathered by distributing the questionnaire as an online survey to students who use distance learning systems at the University of Belgrade. The students filled out the questionnaire during the first months of the COVID-19 pandemic period in 2020. The oldest and the biggest university students in Serbia (the University of Belgrade) were selected with random sampling. The survey included 1,254 respondents who correctly completed the questionnaire. After closing the survey, we conducted the data analysis process. To test the hypotheses and predict the model constructs, SPSS and AMOS v.22.0 statistical software were used.

The Measurement Model

The measurement model aims to determine the measurement instruments' internal reliability, discriminant, and convergent validity. Nunnally (1978) considers that internal consistency is confirmed if the value of Cronbach's Alpha is more than 0.6. The results depicted in Table 1 indicate that the analysed model's internal consistency values are acceptable. Average Variance Extracted (AVE) was applied to evaluate convergent validity. The value of AVE should be high than 0.5 (Fornell & Larcker, 1981). The results of convergent validity (Table 1) are also acceptable in this study. Besides, discriminate validity was also obtained. That indicates that the calculated values of the AVE's square root for each construct are higher than correlations between two specific constructs (Fornell & Larcker, 1981; Anderson & Gerbing, 1988). The discriminate validity values are displayed in Table 1 with bold numbers on the diagonal. Confirmatory factor analysis (CFA) was conducted in this study to assess the validity of the variables. The value of standardised item loading for each metric is more than 0.5, with p-values less than 0.001. This also confirmed the validity of the instrument. The relative chi-square value for the defined measuring model is 2.87, which is below the required limit of 3, indicating that this model has an acceptable fit. Several different model indices of fit were evaluated, including the RMSEA, where excellent model fit was suggested by values less than or equal to 0.06. The value of RMSEA, in this case, is 0.06, which further suggests that the model fit is adequate. The obtained values of NFI-0.93; RFI-0.91; IFI-0.95; TLI-0.95; CFI-0.95 indicate a good model fit, which is in accordance with Hooper et al. (2008), where accepted values are between 0.90 and 0.95. Therefore, construct validity and reliability in the measurement model are achieved, and structural model analysis is presented in the following section of the paper.

Table 1. The reliability and validity of the defined model

Construct	Item loading	Cronbach Alpha	CR	AVE	Authority	Simplicity	Quality
Authority (A)							
A1.	0.535						
A2.	0.713	0.689	0.689	0.428	**0.654**		
A3.	0.700						
Simplicity (S)							
S1.	0.707						
S2.	0.593						
S3.	0.806	0.824	0.825	0.502	0.625**	**0.709**	
S4.	0.708						
S5.	0.712						
Quality (Q)							
Q1.	0.777						
Q2.	0.810						
Q3.	0.778	0.833	0.889	0.577	0.676**	0.609**	**0.760**
Q4.	0.512						
Q5.	0.803						

** *p-value<0.001*

The Structural Equation Model

In the next step, SEM was employed to test the hypotheses. This technique is utilised to analyse the structural relationship among constructs (latent and observed) (Sheykhfard & Haghighi, 2020). A goodness-of-fit model was achieved ($\chi 2$/ df-2.42; RMSEA-0.067; NFI-0.94; RFI-0.92; IFI-0.97; TLI-0.95; CFI-0.96), and all fit indices in the structural model are satisfactory and fit well. To test relationships between the constructs, Figure 2 depicts factor loadings and standardised coefficients evaluated in the SEM. Standardised path coefficients were calculated to verify each construct's significance in the path model and presented in Table 2. To assess the linear dependencies between the dependent and independent variables, the analysis of variance (ANOVA) method was performed. Variables such as Information Accuracy and Information Security were used as independent variables. The dependent variable presents the calculated average values of the answers of the group of questions within *Quality of E-learning*. The main parameters of which ANOVA consist are: the sum of squares of parameters, degree of freedom (df), mean of squares, F-ratio of parameters and statistical significance (p-value) (Arsić et al., 2019; Özakın & Kaya, 2020). Table 3 shows that *Information accuracy* and *Information security* have linear relationships with the *quality of E-learning*.

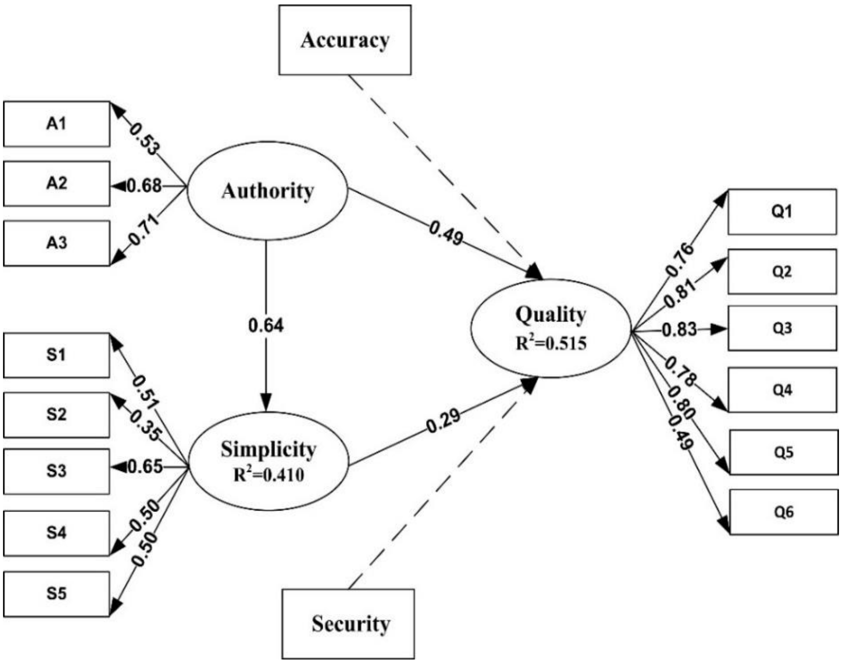

Figure 2. The results of the Structural Equation Model

Table 2. The results of SEM

Hypothesis	Standardized weights β	Estimate	SE	t - value	Conclusion
H1: A → Q	0.494	0.371	0.072	5.181**	Accepted
H2: A → S	0.640	0.601	0.073	8.215**	Accepted
H3: S → Q	0.293	0.234	0.060	3.296**	Accepted

***p-value<0.001*

Table 3. The results of ANOVA

			Sum of Squares	df	Mean Square	F-test	p-value
Accuracy-Quality	Between Groups	Combined	222.352	4	55.588	87.261	0.000
		Linearity	95.623	1	95.623	150.107	0.000
		Deviation of linearity	16.227	3	5.409	8.491	0.000
	Within Groups		795.654	1250	0.627		
Security-Quality	Between Groups	Combined	100.612	4	25.153	34.245	0.000
		Linearity	76.209	1	76.209	10.756	0.000
		Deviation of linearity	17.153	3	5.718	7.785	0.000
	Within Groups		917.394	1250	0.735		

ANN Modelling

The Artificial Neural Network (ANN) was developed by Haykin (1994) and defined as "a massively parallel and distributed processor composed of simple processing units" (Xu et al., 2019, p. 4), which have a neural propensity to accumulate data and knowledge from the experiment, making it available for use. The most important ANN algorithm element is a multi-process information processing system that employs simple processing elements with a high level of mutual connection (Bayar et al., 2009). These processing elements, commonly called neurons, work in line with solving certain problems. A Multilayer Perceptron (MLP) back propagation feed forward method is employed in this study. The MLP is the most utilised and popular ANN method (Sohaib et al., 2020; Yakubu et al., 2020), which was developed in the defined model by using the software SPSS 22.0.

The artificial neural network consists of three layers of neurons, such as the input, hidden, and output layers, including the number of neurons to process separately for each layer. Neurons of the input layer represent information about the input parameters such as the Simplicity of E-learning, the Authority initiative, the Information Accuracy, and the Information Security, which in the ANN model represents independent (exogenous) variables. Four neurons represent the hidden layer, while the only neuron in the output layer produces the output information presented in the model as an indicator of the *Quality of E-learning*, as a dependent (endogenous) variable (Figure 3).

In this study, ten iterations were performed to cross-validate the model (Table 4) until the error between the measured output (*Quality of E-learning*) and the calculated value was minimised and remained constant, according to the recommendation of different authors (Hammerstrom, 1993; Goh, 1995). Hence, model training was performed with 72.7%, while 27.3% was used for model testing. The synaptic weights of the input neuron on the hidden and output neuron are shown in Figure 3.

Exactness can be measured by the root mean square error (RMSE), where the ANN was validated by calculating RMSE in both the training and testing datasets (Sharma et al., 2017). The RMSE is computed using equations (1) and (2), where SSE is „the sum of squared error and MSE is the mean squared prediction error" (Sohaib et al., 2020, p. 13143).

$$MSE = 1/n * SSE \tag{1}$$

$$RMSE = \sqrt{MSE} \tag{2}$$

The obtained values of RMSE in ten iterations of the training and testing model are depicted in Table 4. Additionally, the mean of the training model is 0.047, and the mean of the testing model is 0.074. The model with a vast number of neurons in the higher layer and with the strongest influences which predicts quality perception, was obtained in the tenth iteration (Figure 3).

Table 4. Results of Artificial Neural Network Model (SEE and RMSE)

Artificial Neural Network	Training (72.7% of data sample 1254) N=912		Testing (27.3% of data sample 1254) N=342	
	SSE	RMSE	SSE	RMSE
ANN1	0.611	0.046	0.762	0.076
ANN2	0.644	0.046	0.654	0.075
ANN3	0.661	0.048	0.797	0.077
ANN4	0.609	0.047	0.682	0.070
ANN5	0.655	0.048	0.646	0.071
ANN6	0.645	0.046	0.723	0.079
ANN7	0.612	0.046	0.730	0.075
ANN8	0.620	0.046	0.745	0.078
ANN9	0.689	0.048	0.610	0.070
ANN10	0.656	0.046	0.593	0.072
	Mean	0.047	Mean	0.074

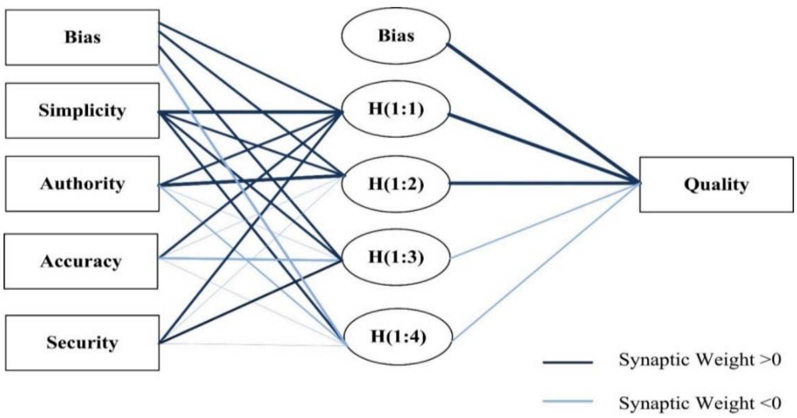

Figure 3. The model of Proposed Artificial Neural Network

Table 5 depicts sensitivity analysis performance. Sensitivity analysis is an important approach for explaining the connection and impact of each input parameter on the research model's outputs (Nourani & Fard, 2012). Sensitivity analysis was computed by averaging the mean significance of the independent variables that can help predict the dependent variable (Chong, 2013). The sensitivity analysis results showed that *Authority initiative* was the most influential independent variable in predicting *Quality of E-learning* perception during the pandemic period. The other important variables that help predict the same construct were the *Simplicity of E-learning*, *Information Accuracy*, and *Information Security*.

Table 5. Independent variables' importance

Constructs	Importance	Normalised Importance
Authority	0.474	100.0%
Simplicity	0.303	63.9%
Accuracy	0.155	32.7%
Security	0.069	14.6%

RESULTS AND DISCUSSION

This paper highlights the extension of the traditional approach based on SEM methodology by integrating it into the ANN prediction method. Our hypotheses were tested using SEM methodology, and the results indicate that all hypotheses can be accepted (H1, H2, H3, H4, and H5). The regression coefficients (β-path coefficients) have positive values within the considered hypotheses. For the analysed hypotheses in the defined model, the following results were obtained. With hypothesis H1, it was assumed that *Authority initiative* significantly and positively influenced *Quality of E-learning* during the pandemic period. The results presented in Figure 2 and Table 2 indicate that the construct of *Authority initiative* has a statistically significant influence on the *Quality of E-learning* ($\beta_{A\text{-}Q}$=0.494; SE=0.072; t=5.181; p-value<0.001). These findings confirm that hypothesis H1 is accepted. These results are in line with the findings of Jung (2010) and Delva et al. (2019). The analysis of the association between *Authority initiative* and *Simplicity of E-learning* during the pandemic period shows that hypothesis H2 is accepted ($\beta_{A\text{-}S}$=0.640; SE=0.073; t=8.215; p-value<0.001). This result correlates with previous claims by Mahdizadeh et al. (2008) and Sørebø et al. (2009). Hypothesis H3 (*Simplicity in E-learning* positively influenced the *Quality of E-learning* during the pandemic period) is also supported because a significant association was obtained between the considered constructs ($\beta_{S\text{-}Q}$=0.293; SE=0.060; t=3.296; p-value<0.001). Tan et al. (2014) point out that ease of use in E-learning can significantly improve the quality of interaction between students and professors. Hypotheses H4 and H5 were tested to determine whether the students who paid more attention to control parameters such as *Information Accuracy* and *Security* afforded a higher value to the *Quality of E-learning*. Based on the results obtained by using the ANOVA method (Table 3), the positive influence of the linear dependence between *Information Accuracy* and the *Quality of E-learning* (H4) with statistical significance was confirmed (F-test=87.261 and p-value <0.000). Finally, a statistical significance in the relationship between *Information Security* and the *Quality of E-learning* was also noticed (F-test=34.245 and p-value<0.000). Based on this, hypothesis H5 is also accepted. The obtained results are statistically significant in both cases, which means the model explains that a higher level of the students' perception of accuracy and security of information has implications for the higher level of perception of the Quality of E-learning. A similar conclusion about the impact of information quality on service delivery quality is found in the research of Alsabawy et al. (2016).

The value of the coefficient of determination R^2 represents the percentage of variance in the dependent variable explained by other variables directly related to it (*Authority Initiative* and *Simplicity of E-learning*). The results point out that the construct *Authority Initiative* explains 64% of the variance of the construct *Simplicity of E-learning*, while the overall model explains 51.5% of the variance in the *Quality of E-learning* during the pandemic period. A similar result is noted in Alla and Faryadi (2013), and Siemens et al. (2017).

The strength of each input predictor (*Authority initiative*, *Simplicity of E-learning*, *Accuracy* and *Security of information*) on the output predictor such as the *Quality of E-learning* is rated employing ANN sensitivity analysis to confirm the SEM results. The ANN findings usually verify the SEM results, which is also the case in this research. The ANN model results depict that *Authority initiative* is the most influential predictor of the *Quality of E-learning*. The same result is presented in the SEM analysis. In contrast, the ANN results show that the *Security of information* predictor is the least influential predictor of the *Quality of E-learning*. The findings indicate that the University of Belgrade ensured student trust and showed an ability to protect privacy before the pandemic. Consequently, the security of information was de facto recognised as the least valuable quality dimension. On the other hand, Jung (2010) points out that professors and other teaching staff are the most powerful influencers of E-learning quality. Their initiatives and activities affect students' academic development in ordinary circumstances (Sutherland & Hall, 2018). Hence, it indicates that the perception in a position of authority remains a significant predictor because competent authorities during the pandemic had to put in additional effort to ensure the continuity and the quality of the teaching process. This integrated SEM-ANN method offers better in-depth findings concerning the relative importance of the input constructs, thus presenting valuable information about the perception of the quality of E-learning during the pandemic period.

CONCLUSION

Although some professors are not inclined to use new digital technologies in a learning environment and offer resistance to their application, pandemic disruptions caused by COVID-19 forced teaching staff to adapt and accept the only available way of E-learning at that moment. One of the most important ways of determining the quality of E-learning is the student perspective. Hence, by integrating methods and techniques, this study intends to identify and predict the factors that affect the perception of the quality of E-learning during pandemics, and to clarify their interrelationships through the perspective of the students of the University of Belgrade. The results showed that *Authority* and *Simplicity* significantly and directly affect the *Quality of E-learning*. A significant and direct impact is also found between control variables *Authority* and *Simplicity*. Nonetheless, mutual dependence is established between *Information Accuracy* and *Quality of E-learning*, and between *Information Security* and *Quality of E-learning*.

According to the literature review, and to the best of the authors' knowledge, this paper's main contribution is the fact that little research has been done on the same or similar topic during the COVID-19 pandemic. This study developed a model by integrating input predictors to the output construct *Quality of E-learning* that enabled the proposed model's predictions. The suggested combination of constructs that predict the *Quality of E-learning* has never been analysed in previous research by applying this methodology, which represents an additional contribution of this study. The obtained findings can also contribute to raising the awareness of the academic community and policy-makers to the necessity of dealing with quality in E-education to a greater extent, especially in emergencies such as pandemics. Furthermore, virtual universities in developing countries such as Serbia may benefit from these findings in raising the quality level of their E-learning during the pandemic and in general. This research has significant implications for higher education institutions' quality assurance of the E-learning system. The study's findings offer important recommendations to decision-makers, service providers, developers, and designers in higher education institutions on evaluating and improving the quality of E-learning. In response to emergencies, it is crucial for decision-makers in the educational system to provide adequate financial and technological resources to support distance-learning projects. Taught by experience in the pandemic, it can be recommended that each university have a quality assurance division to control and improve the quality of the E-learning process continually, given that changes are expected in our world.

Exploring the perception of quality in the age of COVID-19 was indeed a challenge for this paper's researchers. It should be highlighted that the research findings are relevant in times of duress. Although the data collection period was short due to the event's topicality, the sample size can still be observed as a limitation of the study. The limitation in terms of questions pertaining to the defined constructs and the constructs themselves is also a recommendation for future directions of research. For example, in defining the simplicity of E-learning during the coronavirus, technical issues faced by professors and students were not considered. Furthermore, research on the relationship between student satisfaction and service quality, and whether they impact student behaviour and intent after the COVID-19 pandemic can be the next step in future investigations. The conceptual model can also be upgraded with new constructs such as quality information, IT infrastructure services, or system quality (technical issue) within the framework of emergency disorders. Comparing the perceptions of teaching staff and students at the time of the pandemic would also be interesting for further consideration. In the end, several issues arise as part of the broader picture. One of them is whether *Simplicity in E-learning*, by inertia, tends to the minimal investment of students' further work efforts. This cognition would potentially influence E-learning quality in the academic communities' future activities.

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ПЕРЦЕПЦИЈА КВАЛИТЕТА Е-УЧЕЊА У ВИСОКОМ ОБРАЗОВАЊУ: SEM-ANN ПРИСТУП

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Резиме

Период пандемије изазвао је мере закључавања широм света које су приморале човечанство на онлајн компензацију у образовном систему. Као резултат, е-учење је постало главно средство наставе и комуникације, и будућност електронског учења зависи од квалитета система за е-учење. Ова студија има за циљ да идентификује и предвиди факторе који утичу на перцепцију квалитета е-учења током пандемија применом ново-интегрисаног SEM-ANN модела. Резултати показују да иницијатива управе факултета има најважнији утицај и значај у предвиђању квалитета електронског учења током пандемија, док најмањи утицај има предиктор „сигурност информација“. Ово истраживање има значајне импликације на високошколске установе у обезбеђивању квалитета система е-учења. Добијени резултати такође могу допринети подизању свести академске заједнице и твораца политике да се више баве квалитетом онлајн образовања, посебно у ванредним ситуацијама као што су пандемије. Виртуелни универзитети земаља у развоју могу имати користи од овог истраживања у смислу подизања квалитета е-учења током пандемија и уопште.