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Assessing Engineering Students' Acceptance of an E-Learning System: A Longitudinal Study*

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Although previous research on the e-learning system acceptance has been conducted using UTAUT, no study followed the longitudinal approach. Accordingly, this research examines the engineering students' (N = 291) e-learning system acceptance by three years of study. The structural equation modelling analysis confirmed UTAUT relationships in each year. Effort expectancy and social influence resulted as significant predictors of behavioural intention in all three years. In contrast, performance expectancy influence got lower in later usage. Altogether, our longitudinal study presented that the UTAUT model has weakened over time. Therefore, we propose extending the UTAUT model in future research to better understand user satisfaction and positively contribute to system acceptance. Our research findings can be used for university leaders to investigate and evaluate any implemented information system acceptance through the years.

Keywords: e-learning; engineering students; UTAUT; SEM; longitudinal study

1. Introduction

Globalisation and the digital revolution are the pillars of new and varied forms of education. These are the factors that provide students with instant access to information [1]. Due to the continuous advancement of technology, a standard definition of the e-learning concept is still debatable. Rodrigues et al. [2] define e-learning as "an innovative web-based system based on digital technologies and other forms of educational materials whose primary goal is to provide students with a personalised, learner-centered, open, enjoyable, and interactive learning environment supporting and enhancing the learning processes." E-learning can change the way of learning and offer new possibilities and attract more learners into the learning environment with its abundance of benefits.

The rapid growth of acceptance of the e-learning systems is fueled by advances in information and communication technologies (ICT), alongside the need for increased access to higher education [3]. In such a competitive environment, keeping in touch with new practices, innovations in education, and technological developments can be crucial. McKnight et al. [4] argue that higher education institutions need to develop a strategy if they are willing to move from traditional to e-learning. The main required aspects to consider for the e-learning implementation are observing students' performance on e-learning platforms and their satisfaction. In this case, the end-users have to focus on adopting emerging technologies and the learning process [5].

Technology application in the teaching and learning process varies on different levels. Learning in the technological environment starts from shallow technical engagement, such as presentations or basic internet usage, through e-learning systems, to virtual or augmented learning environments. Factors influencing the level of application of technology have a wide range – from social to facilitating factors. Researches must be conducted within educational institutions to understand how educators and students perceive technology's effects and how they influence education. To be able to examine the real impact of e-learning on the learning process and satisfaction of end-users, years of research are needed.

This paper is underpinned by three years of thorough research and a literature study on adoption, acceptance, and e-learning system usage. For research purposes, the Unified Theory of Acceptance and Use of Technology (UTAUT) has been used. The data were collected from 291 engineering students from the University of Novi Sad. Three out of five hypothesised relationships between six acceptance variables are significantly supported during the three years of study. Our research findings can be used for university leaders to investigate and evaluate any implemented information system acceptance through the years.

2. Theoretical Framework

This paper's literature study is part of a systematic literature review carried out on a broader topic –

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digital transformation in education. E-learning, as a subtopic, has a great place in this literature review.

2.1 E-Learning Concept

In the last few years, e-learning, as one of the most important consequences of technological innovations, became a *sine qua non* for maintaining the university competitiveness. E-learning gives the learning providers and students an unprecedented opportunity to access more learning experiences without time, space, or place limitations. Since e-learning is developed for learning, it should fit with the students' learning expectations as much as possible. There are findings [6] that claim if an e-learning system does not match the students' expectations, they will likely fail to learn in such an order. Recently, e-learning has become widely used in educational institutions and industries since it benefits the user.

There are different perspectives to observe the benefits of e-learning, such as students' perspective, teachers' perspective, or institution that has implemented this system. E-learners can independently read the materials posted on the Internet and then test the acquired knowledge. This makes the e-learning system an efficient environment [7].

In their study, researchers presented if both students' and instructors' attitudes toward e-assessment remain positive, the overall idea about the expected benefits will be realized [8].

Concannon et al. [9] conducted qualitative research to look at the positive and negative factors of technology usage in education. As the benefits, they noted the ease of access to resources and the central area's provision for students to access and find information. Negative factors were mostly technical problems.

In the article published in the Journal of Information Technology Education [10], the authors measured the economic benefits of e-learning. They pointed out many advantages of e-learning, from savings to learning advantages compared to other teaching methods. E-learning provides a way for the industry to increase the efficiency and effectiveness of conducting on-the-job training and education [11].

Researchers use different models to measure the acceptance of e-learning system. In general, information systems acceptance is determined by the behavioural intention of users [12]. For the past thirty years or so, researchers have been debating the success of information systems. As a separate field of research, models that measured the acceptance of technology stood out. Taherdoost [13] pointed out many popular theories and models for measuring technology acceptance. Theory of Reasoned Action (TRA) [14] is a model in which any human behaviour is predicted and explained through attitudes, social norms, and intentions. Many other models are an extension of TRA, such as the Theory of Planned Behaviour (TPB) and Technology Acceptance Model (TAM) [15]. TAM is a model proposed by Davis and is widely used to determine whether the information technology users are willing to accept the technology.

Of the several theories that address technology acceptance, this study uses the Unified Theory of Acceptance and Use of Technology. In 2003, Venkatesh, Morris, Davis, and Davis [16] developed the UTAUT based on eight previously developed technology adoption research theories.

2.2 UTAUT

The key constructs of UTAUT presented in Fig. 1 are [16]:

- performance expectancy (PE),
- effort expectancy (EE),

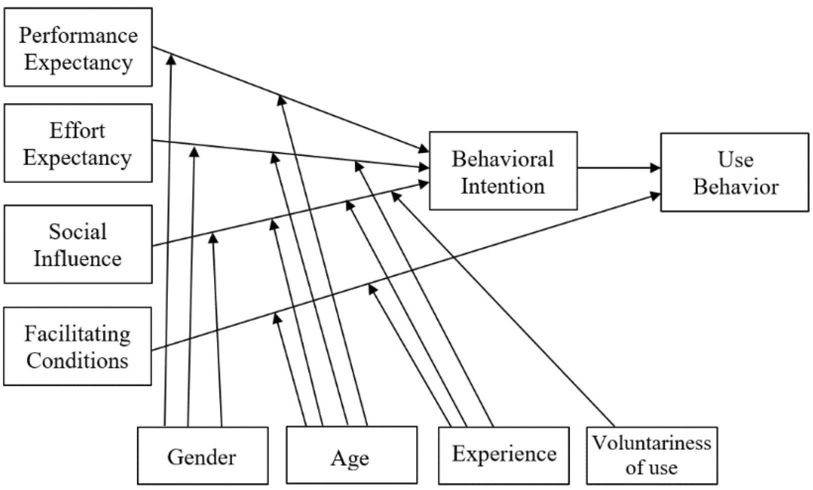

Fig. 1. Unified Theory of Acceptance and Use of Technology (UTAUT) [16].

- social influence (SI), and
- facilitating conditions (FC).

Performance expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" [15, 16]. Effort expectancy is defined as the "degree of ease associated with the use of the system" [15, 16]. Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" [15, 16]. Facilitating conditions are defined as "the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system" [15, 16].

UTAUT has been applied and used in different contexts and therefore has many extensions and modifications. Venkatesh, Thong, and Xu [17] reviewed and synthesised the information systems literature on UTAUT from September 2003 until December 2014 and presented the original paper's large number of citations and extended models based on UTAUT.

UTAUT2 [18] is an extended unified theory of acceptance and use of technology, invented by Venkatesh, Thong, and Xu. In this model, user class is expanded with silent users and social users, as well as new attributes such as hedonic motivation, habit, and price value. Many papers examined how UTAUT constructs affect behavioural intention (BI) and use behaviour (UB) [24, 25, 45, 46].

Performance expectancy was found to have a strong and positive effect on behavioural intention in South America [19]. Many authors confirmed a statistically significant relationship between performance expectancy and behavioural intention [19, 20]. While testing mobile learning, some authors represented the result of a substantial and robust connection between these factors [21, 22].

Effort expectancy positively affects behavioural intention, but many authors also claim that it is the most influencing determinant of behavioural intention to use an e-learning system [15, 23–26]. A significant relationship was found between these two factors [21, 22, 27]. On the other side, some authors have found that the relationship between effort expectancy and behavioural intention is weak and does not have statistical significance [20].

Many authors concluded that social influence positively affects behavioural intention [16, 18–20, 23, 27]. In their research, Abdekhoda, Dehnad, and Gavani [21] claim if social influence increases, the behavioural intention will increase by 24%. Social influence plays the most crucial role in affecting behavioural intention in the learning context of some researches [22]. Authors [23] state that undergraduates are significantly impacted by how his/her colleagues opine about e-learning system usage and satisfaction. Lecturers' or instructors' influence on the e-learning system usage has an impact as well. Some researchers examined the acceptance of the m-learning concept and have concluded that a relationship between these two factors exists, and it is statistically significant and strong [21, 22]. Other researches showed no influence of SI on BI [24]. Some authors [25, 45] claim facilitating conditions significantly affect students' usage behaviour, while some claim it doesn't [25].

Even though there are researches on the acceptance of e-learning systems using the UTAUT model, as far as we are aware, no longitudinal studies are examining this topic by using the UTAUT model. With this study, we aim to apply the UTAUT model for investigating the acceptance of technology in case of continuous usage of e-learning for a certain, longer period.

2.3 E-learning in Education

Numerous studies have been conducted to measure student satisfaction and performance at the university level in developed parts of the world. Various factors have been identified that can potentially affect the students' satisfaction with the universities' different education services.

In 2012, Chen [26] conducted an empirical study to examine the proposed new model for e-learning acceptance, integrating educational compatibility with the UTAUT model. Chen concluded that better learning conditions are the basis for satisfying the students' technological expectancies and enhancing their learning performance. Kasse and Waswa [27] studied UTAUT to check the acceptance and adoption of e-learning in higher education facilities in Uganda. The cross-sectional qualitative study revealed that UTAUT provided inputs and insights regarding the acceptance and assessment of the usage of e-learning. This model was found usable to access the adoption of e-learning. The study taken at Princess Nourah Bint Abdulrahman University (PNU) in Riyadh, Saudi Arabia [28] indicated that faculty and students' perspectives were generally favourable toward e-learning. Faculty and female students showed high awareness of the potential benefits of e-learning to enhance current teaching and learning practice. The greatest obstacle reported was the limited technological infrastructure to support e-learning, including Internet connections, technical support, computer laboratories, digital resources, and the use of appropriate Learning Management Systems (LMS). Sabraz and Rustih [23] conducted a study on undergraduate and postgraduate students from fifteen Sri Lankan state universities. Results indicated that students who already use technology do not need extra training to use the e-learning system. They used the UTAUT2 model for research purposes. It was found that constructs of UTAUT2 have a significant impact on and play an important role in behavioural intention and system usage of the e-learning system. The study [29] conducted in a Postgraduate Program at Universitas Negeri Makasaar in Indonesia evaluated e-learning acceptance through the UTAUT model. Hypothesis tests showed that PE, EE, FC, and SI had significantly positive effects on BI for e-learning acceptance. Mehta et al. [30] proposed the link between Schwartz's theory of human values and UTAUT2 to develop the Value-Enhanced Technology Adoption Model of professional e-learning in Gambia and the UK. They found no relationships between values associated with security, conformity, and power and adoption model for e-learning. However, they found that "learners who prioritise self-enhancement values and therefore prioritise their achievement perceive e-learning as worthwhile and that their social environment endorses e-learning use".

2.4 E-Learning in Engineering Education at the University of Novi Sad

Faculty of Technical Sciences (University of Novi Sad, Serbia) is advancing engineering studies by applying innovations in study programmes. Some programmes are continuously developed and upgraded due to industry expectations, such as Information System Engineering [31]. Besides improving study programmes, the Faculty of Technical Sciences is continuously working to improve the teaching process. The Department of Industrial Engineering and Management at the Faculty of Technical Sciences, University of Novi Sad, established an e-learning system based on Moodle called "Moodle eLLab" to improve the complete learning process in conventional studies on engineering study programmes. The idea behind was to create a new way of learning and implement an entirely new framework composed of different learning approaches for engineering students. A similar approach was presented at the University of Toronto [32]. Moodle eLLab was extended in 2019, from the department e-learning system to the whole University of Novi Sad and is now called "Sova". All functionalities are preserved, and only the visual design was improved. Users of this e-learning system, depending on the course they approach, can be teachers, assistants, course managers, students, administrators, or guests.

At the University of Novi Sad, implementing e-learning in education is still ongoing and not fully complete. However, several studies deal with this topic.

Marjanovic et al. [33] proposed an integrated model for evaluating the effectiveness of Social networking sites (SNSs) from an engineering student's point of view. In 2018, the SNA method application was examined in LMS (i.e., Moodle) at the University of Novi Sad. The research was conducted in a course on e-business at the study program of Information Systems Engineering. In this study, Rakic et al. [34] measured the relationship between the students' performances and the usage frequency of educational resources from the e-learning platform. Their analysis showed that the use of resources is an essential factor in forming students' overall success. Authors claim that students who achieve the same or similar performance use similar educational resources. Their previous research [35] showed that if a student uses more resources available on the e-learning platform, they have higher grades.

Another research [36] explored the evaluation of student success at the e-learning platform. The authors used a multi-method approach to data analysis. The study was conducted with students at the Faculty of Technical Sciences, University of Novi Sad. The results showed a significant relationship between the use of e-learning in education and students' performance.

Research that was carried out in 2019. by Lolic, Ristic, Stefanovic, and Marjanovic [37] at the Faculty of Technical Sciences, the University of Novi Sad examined the acceptance of the e-learning system by students. In this research, a strong connection within all UTAUT constructs was found, except the relationship between behavioural intention and system usage.

Another research that represents an empirical study of factors influencing students using the e-learning system was conducted in 2019 [24]. Performance expectancy, effort expectancy, and facilitating conditions confirm their influence on behavioural intentions. In contrast, social influence does not affect the behavioural intention of students' intention to use the e-learning system according to this study.

Following the aforementioned and with the aim of investigating the e-learning system acceptance for a certain, longer period, our study aims to answer the research question – *How is the e-learning system accepted among the engineering students in the three years observation?*

3. Research Method

Three longitudinal field studies were conducted to test UTAUT. Within this section, materials and methods that have been used for the research are shown.

3.1 Participants

The research participants were higher education students from the Engineering Schools of the University of Novi Sad. The study took a longitudinal approach for the research, intending to access the e-learning system acceptance and students' continuance in system usage, therefore examining three years in a row. Since the number of respondents varies within the studied years, random sampling was undertaken to select a sample that reflected students' profiles, with the final number of 291 students from each year. Prior to selecting the random 291 students, a non-engaged bias setting was conducted. The descriptive data are summarised in Table 1.

3.2 Measurement Scales

Data collected through an online survey, from June to July, at the end of 2017, 2018, and 2019. academic years covered six constructs related to students' acceptance and use of the technology.

PE, EE, SI, and FC were measured on a 5-point Likert scale with response categories recorded as 'strongly disagree' (1), 'disagree' (2), 'neutral' (3), 'agree' (4), and 'strongly agree' (5). The scale items to assess the key constructs, including PE, EE, SI, and FC, were developed and modified from Venkatesh et al. (2003) [16].

We set five items on PE, EE, and SI to measure the degree to which students expect use will promote their academic performance and thus influence their intention for using the system. Moreover, we also set five items on FC and three items on BI to measure the degree to which students believe that using the e-learning system will be useful in their learning and affect UB. Eleven items, which have

Table 1. Demographic characteristics

Variable	Classification	Number / Percentage (N = 291)		
		T1_2017	T2_2018	T3_2019
Gender	Female	134 / 46	179 / 61.5	179 / 61.5
	Male	157 / 54	112 / 38.5	112 / 38.5
Age	Less than 21	91 / 31.3	129 / 44.3	137 / 47.1
	Between 21 and 24	133 / 51.2	149 / 51.2	136 / 46.7
	Between 25 and 30	46 / 15.8	12 / 4.1	16 / 5.5
	More than 30	21 / 7.2	1 / 3	2 / 7
Computer Literacy	Professional	85 / 30.9	90 / 30.9	76 / 26.1
	Advanced	190 /62.2	181 / 62.2	190 / 65.3
	Beginner	16 / 6.9	20 / 6.9	25 / 8.6

Table 2. Measured constructs descriptive data

Constructs	No of Items	Mean	SD	Skewness	Kurtosis	α
T1_PE	5	4.110	0.765	–0.713	0.155	0.892
T1_EE	5	4.533	0.561	–2.125	8.589	0.864
T1_SI	5	3.269	0.878	–0.194	–0.236	0.785
T1_FC	5	4.226	0.679	–0.868	0.484	0.787
T1_BI	3	4.245	0.932	–1.374	1.826	0.961
T1_UB	11	3.182	0.982	–0.079	–0.740	0.902
						0.916
T2_PE	5	4.350	0.624	–0.669	–0.037	0.835
T2_EE	5	4.711	0.473	–3.301	16.800	0.849
T2_SI	5	3.506	0.764	–0.082	–0.077	0.697
T2_FC	5	4.421	0.519	–0.701	–0.291	0.638
T2_BI	3	4.601	0.624	–1.807	3.886	0.936
T2_UB	11	3.439	0.879	0.056	–0.889	0.874
						0.887
T3_PE	5	4.371	0.648	–0.810	0.051	0.851
T3_EE	5	4.716	0.451	–2.721	11.769	0.828
T3_SI	5	3.567	0.801	–0.255	–0.252	0.733
T3_FC	5	4.423	0.571	–0.884	0.080	0.705
T3_BI	3	4.604	0.655	–1.890	3.863	0.939
T3_UB	11	3.614	0.744	–0.055	–0.791	0.824
						0.879

been modified and finally developed from authors [1, 32], were set on UB. Students have been asked how frequently they use the e-learning system for different assignments and tasks during the past three years. Use was measured on a 5-point Likert scale with response categories recorded as 'never' (1), 'rarely' (2), 'sometimes' (3), 'frequently' (4), and 'always' (5).

The descriptive statistics of all the constructs measured in the model are summarised and presented in Table 2.

The results show that all measured constructs increased over time. Accordingly, skewness and kurtosis indices of almost all constructs were less than absolute 1, which testifies the data is normally distributed. However, a deviation from the normal distribution in the case of some variables is noticeable. Factors EE and BI had skewness and kurtosis indices values more than absolute 1 in all three observed years. Such differences will be expressed in factor analysis and may result in the omission of some manifest variables, which will be presented in further analysis within this paper.

4. Results

To explore students' acceptance and continuance of use, the dataset was used to test a longitudinal model. After the data collection process was completed, the results were analysed with the IBM SPSS tool and presented in the following part of the paper.

Exploratory Factor Analysis (EFA) was used to identify the factors structure by examination of correlation matrices. Accordingly, Confirmatory Factor Analysis (CFA) was used to statistically confirm the definition of dimensions by manifest variables in AMOS (Analysis of Moment Structures) software. This analysis was used to test the conceptual model and hypothesis.

4.1 Analysis of the Measurement Model

With the aim to improve the validity of the model by using EFA, the next steps were conducted:

1. Applying the Keizer-Guttman's rules or ''validity of variance higher than 1''.
2. Screen Plot – the visual representation of variance value.
3. Eliminating the variables that made other factors not crucial for this research.
4. Assessing the model fit through the following indices: a nonsignificant χ^2, goodness-of-fit index (GFI), comparative fit index (CFI), root-mean-square of approximation (RMSEA), and chi-square to degrees of freedom ratio (χ^2/df) [38].

In Table 3, the acceptable values of these indices and their values in the measurement model for all observed years were presented. The proposed measurement models were considered to have a good model fit. The reliability of measurement instruments was determined by calculating a coefficient of Cronbach's alpha for each dimension (see Table 2).

Regarding convergence, the factor loading values in all three measurement models were significant and ranged from 0.520 to 0.914. Since all the values exceeded 0.5, according to Hair et al. [39], that demonstrates adequate convergent validity at the item level. Reliability and convergent validity of factors were estimated with a usage of Composite Reliability (CR) and Average Variance Extracted (AVE). The results are demonstrated in Table 4.

Table 3. Measurement model fit indices

Model goodness fit indices	Recommended level of fit	Measurement model		
		T1_2017	T2_2018	T3_2019
χ^2	Not significant	Not significant	Not significant	Not significant
GFI	> 0.90	0.893	0.911	0.904
CFI	> 0.90	0.966	0.962	0.956
χ^2/df	< 5	1.581	1.704	1.754
RMSEA	< 0.08	0.045	0.049	0.051

Table 4. Validity and Reliability

Factor	T1_2017				T2_2018				T3_2019			
	CR	AVE	MSV	ASV	CR	AVE	MSV	ASV	CR	AVE	MSV	ASV
PE	0.899	0.693	0.296	0.220	0.837	0.635	0.257	0.113	0.847	0.651	0.190	0.115
EE	0.816	0.608	0.295	0.152	0.905	0.705	0.216	0.078	0.863	0.568	0.265	0.113
SI	0.827	0.570	0.229	0.147	0.793	0.583	0.257	0.093	0.804	0.598	0.190	0.078
FC	0.777	0.545	0.307	0.234	0.741	0.514	0.216	0.073	0.736	0.491	0.265	0.106
BI	0.961	0.891	0.307	0.203	0.937	0.833	0.123	0.085	0.940	0.840	0.147	0.107
UB	0.902	0.507	0.113	0.066	0.837	0.508	0.085	0.041	0.816	0.474	0.085	0.037

Average variations are above the recommended 0.50 level [40], which means more than half of the observed variables as indicators were calculated with their factor's hypothesis. As presented in Table 4, only T3_FC and T3_UB have AVE slightly under the recommended level (0.491 and 0.474). Nevertheless, both T3_FC and T3_UB have more than adequate alpha values, therefore indicating good internal consistency. Likewise, FC and UB at T3 have appropriate composite reliability; thus, they were included in the study. CR was higher than AVE for each factor; therefore, we can conclude that all factors in the measurement model have adequate convergent validity.

Discriminant values can be estimated by testing AVE, MSV, and ASV. By Hair et al. [41], if MSV is higher than ASV, it leads to discriminant importance. For discriminant validity to be adequate, AVE's square root for a construct should be higher than the correlation between the construct and any other construct in the measurement model [42]. All the constructs had adequate discriminant validity. Summarised, models of measurement had adequate reliability, convergent validity, and discriminant validity.

4.2 Analysis of the Structural Model

Based on the CFA, a Structural Equation Modeling (SEM) [38] has been conducted. In Table 5, the values of suitability indexes are presented.

GFI values at T1 and T3 were slightly under the proposed boundary of 0.9. Nevertheless, some previous researches [47, 48] demonstrated that the adjusted GFI and GFI indices tend to be low in simulation models, and thus 0.9 should only be a rough guideline. Eventually, since the values of χ^2/df satisfy the defined criteria and the GFI values were just slightly below the model's recommended level fit together with all other values that are in the acceptable range, the proposed structural models were considered to have an adequate model fit.

The hypothesised model was examined with a three-wave longitudinal survey: T1_2017, T2_2018, and T3_2019, of 291 students from the Engineering Schools of the University of Novi Sad. As shown in Fig. 2, the results of a SEM analysis of the survey data confirmed the hypothesised model in all three years. The five proposed hypotheses were tested three years in a row.

Table 6 summarises the SEM analysis results for the longitudinal model, including path coefficients,

Table 5. Structural model fit indices

Model goodness -fit indices	Recommended level of fit	Structural model		
		T1_2017	T2_2018	T3_2019
χ^2	Not significant	Not significant	Not significant	Not significant
GFI	> 0.90	0.887	0.904	0.895
CFI	> 0.90	0.961	0.956	0.950
χ^2/df	< 5	1.669	1.795	1.843
RMSEA	< 0.08	0.048	0.052	0.054

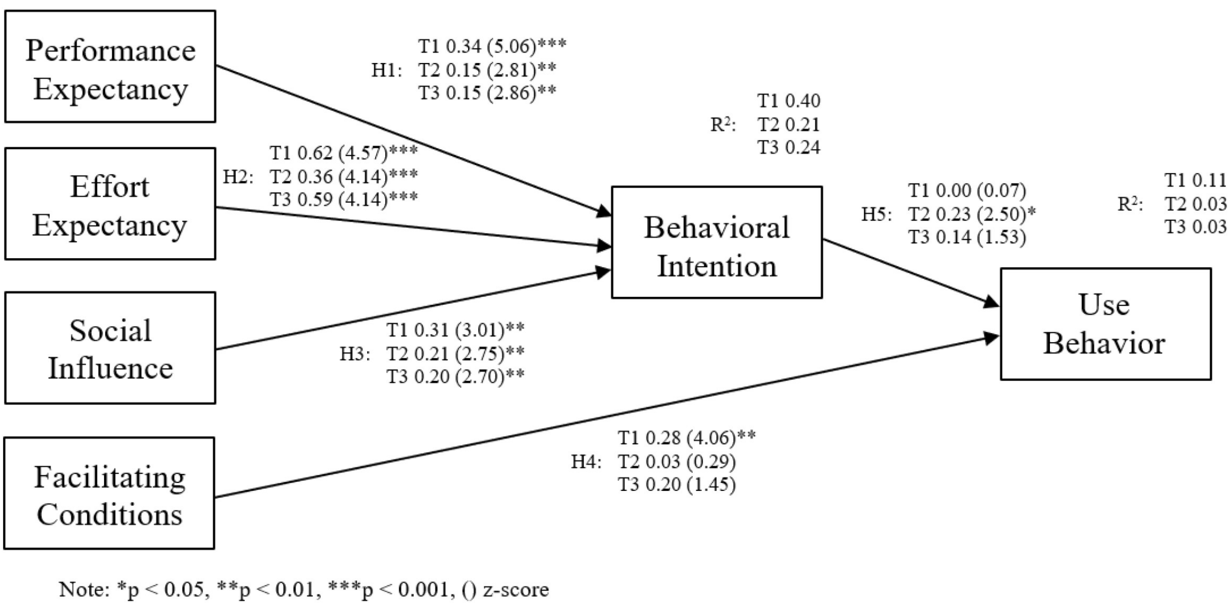

Fig. 2. Hypotheses testing results.

Table 6. Summary of hypotheses testing results

Hypothesis	Path	Path coefficient	Result
T1_2017			
H1	PE → BI	0.337***	accepted
H2	EE → BI	0.621***	accepted
H3	SI → BI	0.310**	accepted
H4	FC → UB	0.283***	accepted
H5	BI → UB	0.004	not accepted
T2_2018			
H1	PE → BI	0.150**	accepted
H2	EE → BI	0.365***	accepted
H3	SI → BI	0.213**	accepted
H4	FC → UB	0.029	not accepted
H5	BI → UB	0.224*	accepted
T3_2019			
H1	PE → BI	0.144**	accepted
H2	EE → BI	0.588***	accepted
H3	SI → BI	0.200**	accepted
H4	FC → UB	0.200	not accepted
H5	BI → UB	0.142	not accepted

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

p-values, and z-results for each dependent variable in each hypothesised link. Within three tested years, major hypothesised relationships are significant at $p < 0.05$. In the initial phase, T1_2017, all relationships were strong and statistically significant, except the link between BI and UB ($\beta = 0.004$, $p = 0.946$). Although results testify students have a strong intention to use the e-learning system (mean value of BI factor is greater than 4.2), that does not eventually affect their use behaviour. With further investigation, we discovered Quiz, Marking of completed activity, Messages, and Participants directory are the least used functionalities of the e-learning system.

Considering the strong students' intention to use the e-learning system, and not having a satisfying result, the authors developed the strategy of improving both system functionalities and students' system usage and satisfaction. After improving the identified gaps in the e-learning system functionalities, the second phase of the longitudinal research, T2_2018, resulted as follows. The relationship between PE and BI ($\beta = 0.150$, $p < 0.01$) has weakened compared to T1, but with EE and SI still produces a significant R2 value of 0.21. Both EE and SI factors have a significant relationship with BI at T2. On the other side, FC showed weak path coefficient ($\beta = 0.029$, $p = 0.775$) to UB. Furthermore, a notable change is presented in the relationship between BI and UB with a path coefficient $\beta = 0.224$, p-value < 0.05. The third instance of the research, T3_2019, showed that the e-learning system still has space for improvements regarding its functionalities.

The overall results from three observed years show that FC's influence on UB has weakened over time, along with BI. Accordingly, BI and FC jointly explain quite a low proportion of UB variance, with 11% at T1, and only 3% in T2 and T3. These results show that the UTAUT model weakens over time.

Nevertheless, the relationships between independent variables PE, EE, and SI with dependent variable BI resulted as significant, and with increased R^2 by 0.24, when compared to T2. These three constructs can contribute to an explanation of BI over time significantly. The relationship between FC and UB was still statistically not significant ($\beta = 0.200$, $p = 0.147$), same as BI's relationship to UB, with a slightly weaker effect than at T2.

This research's primary goal was to determine students' continuance of the e-learning system use by longitudinal exploration. Furthermore, the goal is to improve the e-learning system acceptance by investigating the results from each year, and accordingly implementing and tracking changes in the system usage over time. Therefore, it was essential to know whether one model can be applied equally to data obtained from two or more years.

The Model Invariance Assessment evaluated the difference between unconstrained and constrained models, which assumes that the groups are not resulting in the parameters' different value when the model is applied to the data [43]. The nested model comparisons' key results were evaluated by a chi-square test (CMIN) (see Table 7).

All the comparisons showed statistically significant results; thus, the variables' correlation differs

Table 7. Model Invariance Assessment

Structural weights	DF	CMIN	P	NFI Delta-1	IFI Delta-2	RFI rho-1	TLI rho-2
T1 – T2	5	15.249	0.009	0.019	0.019	–0.088	–0.091
T1 – T3	5	11.640	0.040	0.014	0.014	–0.103	–0.107
T2 – T3	5	2.382	0.794	0.003	0.003	–0.160	–0.167

between the groups, and the research question will be explained for each group separately.

5. Discussion

As presented in Fig. 2, the path coefficients from PE, EE, and SI tested are proved to be significant predictors of BI. Likewise, FC and BI are essential predictors of the UB in observing the students' e-learning system usage in the three-wave longitudinal study. These results were obtained in prior studies, as well [19, 21, 44].

The use of structural equation modelling tools identified differences in the aforementioned relationships between three investigated groups; however, no differences occurred in testing the measurement invariance between years, assuming their structural weight to be equal.

Fairly most hypothesised links among the model's variables are supported, except the relationship between BI and UB at T1 and T3, and FC and UB at T2 and T3. Performance expectancy has long been the key predictor of users' behavioural intention to use technology. Previous results testify that PE is one of BI's strongest predictors and indirectly influences use behaviour [19, 21, 26]. With respect to the PE-BI link, the results of this study showed that PE influence has weakened over time. This result can be related to the fact that students gained knowledge in the e-learning system usage during the observed years, and thus they know how it will eventually influence their learning. However, the EE and SI were kept significantly and directly related to BI in all three longitudinal study waves. As far as the FC's direct influence on UB is concerned, previous studies have shown both significant [44] and not significant relationships [19, 21].

Our results differ from year to year. Namely, the FC-UB link outcome was significant at T1 (β = 0.283, $p < 0.001$). Yet, at T2, the path coefficient between FC and UB has strongly weakened and resulted in only 0.029, p-value = 0.29; therefore, the proposed hypothesis was rejected at the second instance of the longitudinal study. Finally, in the third instance of the study, T3_2019, the relationship between FC and UB has strengthened (β = 0.200, p = 1.45). However, it is still kept as a statistically not significant predictor of UB.

In 2017, e-learning system acceptance was observed from the end-user perspective, to investigate whether the implemented system, presented as new technology, was successful and accepted by students. The study resulted in the approval of 4 from 5 proposed hypotheses. The most crucial relationship between BI and UB was the weakest of all suggested links (β = 0.004, $p < 0.05$). This result has empowered further investigation of the system usage and improvement strategy development. Although most of the system functionalities have been developed, quite a lot of them have never been used, as seen from students' answers. This situation has led to the system functionalities improvements to produce an overall increase in the students' intention to use the system and system usage accordingly.

The second instance of the longitudinal study, the year of 2018, has resulted in an apparent increase of the significance between the BI-UB, with path coefficient β = 0.224, p-value < 0.05. This evidence affirms improvements in the students' behavioural intention and system usage.

Finally, the third instance of the study presented this relationship as not statistically significant (β = 0.142, p = 1.53). Thus, it testifies the students' behavioural intention influence on the system use has weakened over time.

Eventually, a model invariance assessment is conducted. Model comparisons assume that the groups are not resulting in the parameters' different values when the model is applied to different data. Overall results show that T1, T2, and T3 are invariant across the time when supposing their structural weight is equal. Nevertheless, assuming the unconstrained model to be correct, the differences in the observations T1–T2 (DF = 5, CMIN = 15.249, p = 0.009), T2–T3 (DF = 5, CMIN = 11.640, p = 0.040), and T1–T3 (DF = 5, CMIN = 2.382, p = 0.749) are noticeable.

To conclude, models are invariant across time; however, the differences in the relationships between supposed factors within models are present, respectively. Altogether, the research results testify the weakening of the observed UTAUT factors and, therefore, open the space to investigate further how to improve the information systems model acceptance.

The findings of the study ought to be interpreted in light of their limitations. The first limitation is our sample. Hence, this study included only the data from the Engineering Schools of the University of Novi Sad. Future studies should include other universities and compare mutual findings regarding the e-learning system acceptance and gain more significant insights from different environments.

6. Conclusion

This paper presents a three-wave longitudinal study on higher education students' acceptance and continuance of the e-learning system usage. The study investigated how UTAUT variables influence e-learning usage outcomes. As far as we are aware, many studies have been investigating the e-learning systems acceptance using the UTAUT model; nevertheless, there are no longitudinal studies related to the topic. Therefore, our study presents a contribution to the related theory.

Based on the Unified Theory of Acceptance and Use of Technology, the proposed model has been confirmed in all three observed years. However, our longitudinal study showed that the UTAUT model strength has weakened over time. The significant effect of EE and SI on BI is presented in all observed years. Hereof getting students to form positive beliefs related to EE and SI is crucial to improve their behavioural intention and consequentially ensure the continuance of the e-learning system use. However, the PE effect on BI has weakened over time. We can address this phenomenon to the fact students gain knowledge in e-learning system usage; thus, they know how their performance will result in their learning. To facilitate students' EE and SI, to keep a strong relationship with BI, it is essential to introduce them to the subject curriculum at the beginning of each semester. That way, they will be familiar with the needs, along with the benefits of using the e-learning system. Moreover, visualising what is expected from them will help organise time and resources for learning. Finally, it will improve their intention to use the system, eventually.

Alongside this paper evaluated how has the importance of the observed factors changed during time. These findings imply that the acceptance of e-learning systems heavily depends on students' behavioural intentions towards system usage; therefore, it is crucially important to continuously track system adoption. Hence, we suggest future research should put more effort into investigating how to improve user satisfaction to influence students' performance positively.

Next, we are fully aware that 2020 has brought us many changes due to the COVID19 pandemic. We are witnessing the transfer from traditional or blended learning to fully online learning using e-learning systems. Accordingly, this research should be repeated in 2021 to investigate the impact of these changes.

Finally, since our research showed the UTAUT model weakness, we propose to extend it in future work. As user satisfaction is one of the most argued factors of the intention and use sustaining continuance in past research, further research should include it together with the observed model. Namely, the presented model should be extended by having the user satisfaction as the essential factor to improve the overall e-learning satisfaction and to ensure the system use acceptance.

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