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Determinants of learning outcomes with online teaching based on students' perception

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Abstract

Background: Research on the topic of determining success of online learning is on the rise. Defining the key success factors, i.e. determinants of online learning success, is extremely important, especially at present as all higher education institutions have been forced to try their hand at teaching with the help of technology.

Purpose: Thus a research examining factors of learning outcomes of online learning was conducted. Learning outcomes were modelled as dependent variable, while the set of independent model variables included: course design, student motivation, student self-regulation and dialogue (instructor-student, student-student).

Study design/methodology/approach: Five research hypotheses were tested by analysing data collected from the students of the University of Novi Sad. A structured questionnaire was employed to collect data on the attitudes of users (students) to online learning. Respondents expressed their views (perception) about statements and valued them on a 5 point Likert scale. The instrument was applied to a sample of 360 responses using PLS structural equation modelling.

Findings/conclusions: All five hypothesis were supported with the analysis, confirming the importance of research from the aspect of contribution to the literature dedicated to identifying the key success factors of online learning. Additional contribution refers to the research conducted in Serbia, i.e. at the University of Novi Sad.

Limitations/future research: A more detailed analysis of the model itself and the possibility of finding the interdependence of constructs that affect perceived learning outcomes and user satisfaction remains as an area for further research.

Keywords: online learning, success factors, learning outcomes, PLS modelling

Introduction

Organizing online learning at higher education institutions became the focus of research in a large number of scientific disciplines with the outbreak of the pandemic. Although the use of online platforms for collaboration and knowledge exchange had existed before, with the onset of COVID-19 pandemic all higher education institutions were forced to adapt to the new situation (Mo, Hsieh, Lin, Jin & Su, 2021, Elneel et al, 2023). The teaching staff, technical support, as well as the students themselves in most cases had had no previous experience with online learning (Ventura-León, Caycho-Rodríguez, Mamani-Poma, Rodriguez-Dominguez, & Cabrera-Toledo, 2022), but during the two years of the pandemic, all were bound to use technology as both a mediator and assistant in sharing knowledge.

Technological advances and digitalization are causing huge changes in teaching practices, forcing the academic world to evolve from the traditional style of one-way teaching and learning, to acquisition or even consumption (Belanche, Casaló, Orús & Pérez-Rueda, 2020).

Distance learning could be defined as an interaction of human and non-human elements that engage in it through platforms in order to acquire knowledge and/or skills (Eom & Ashill, 2016, p. 186). More precisely, distance learning should be understood as education that uses one or more technologies to deliver instruction to students who are separated from the instructor, and to support regular and substantive interaction between the students and instructor synchronously or asynchronously (Vidergor, H., 2023, p. 2). It is necessary to monitor the quality of distance learning, and the two most often emphasized learning goals listed in research papers are: distance learning outcomes (Fandos-Herrera, Jiménez-Martínez, Orús, Pérez-Rueda & Miguel Pina, 2023; Verstege, Pijeira-Díaz, Noroozi, Biemans, & Diederen, 2019; Kauffman, 2015), and user satisfaction (Bacci, Fabbricatore, & Iannario, 2022; Dai, Teo, Rappa & Huang, 2020; Gopal, Singh & Aggarwal, 2021; Eom, Wen & Ashill, 2006).

All tools that are digitized and provide learning opportunities using learning materials such as: texts, images and video clips, enabling personal pace of learning are characterized with terms *e-learning*, *m-learning* or *distance learning* in the literature (Basak, Wotto & Bélanger, 2018). The main difference between e-learning and distance learning is the isolation that is the main characteristics of distance learning, while e-learning could be lectured in classroom or internet lab.

By defining the basic characteristic of e-learning as constructing knowledge, we clearly opt for the constructivist model, which implies that knowledge is created, as opposed to the objectivist, or behaviourist model (Piaget, 1977; Wang Hu, Li & Yu, 2021). Models that rely on or derive from the constructivist model are: collaboration, socioculturalism, cognitive information processing model, discovery learning, and facilitated learning (Eom & Ashill, 2016). A common feature of all these models is that knowledge is created through e-learning, but they don't agree on how the knowledge is best constructed (from the ultimate individualism of the student, to collectivism).

The paper is based on a constructivist assumption, and a systematic overview of the basic assumptions and implications (Eom & Ashill, 2018). According to this point of view, e-learning is an open system with three entities (students, instructor, and learning management system (LMS)) that are in constant interaction with each other and with the surroundings, with the goal to optimize output in the form of learning outcomes and satisfaction. The system is derived from the Virtual learning environment (VLE) effectiveness model of Piccoli, Ahmad and Ives, 2001. Linking the described system with the framework of technology-based learning (TBL) (Loderer, Pekrun & Lester, 2020) an instrument was created that was applied to the student perception (Alavi, & Leidner, 2001). That research was conducted in the Midwestern United States (Eom & Ashill, 2016), which inspired the research presented in this paper.

Research has shown numerous contributors to successful online learning. Motivation as one of the main antecedents of participation aside, perceived learning support, such as structured course design and effective interactions with instructors and peer learners, was proven to contribute to successful online learning (Albelbisi, Yusop & Selleh, 2018). Previous studies have identified that motivation, perceived learning support, learning engagement, and self-regulated learning strategies are vital factors for successful distant learning (Littlejohn, Hood, Milligan & Mustain, 2016)

The aim of this exploratory research study is to examine the interplay between motivation, student self-regulation, dialogue, course design, and perceived learning outcomes. We propose a research model that involves all variables measured in order to explain individual perceived learning outcomes in distance learning in Serbia (see Figure 1).

1. Factors that contribute to online learning success

Within this paper we examine the attitudes of students of the Faculty of Technical Sciences and the Faculty of Economics, University of Novi Sad, regarding the achieved learning outcomes during distance learning. Respondents gave their opinion (perception) about the independent variables of the model, which included: student motivation, student self-regulation, dialogue (instructor-student,

student-student) and course design; as well as about the dependent variable - learning outcome. We tested our research hypotheses through the analysis of data collected from a sample of 360 students from the University of Novi Sad.

The main goal of this paper is to examine the attitudes of students of the University of Novi Sad towards online classes, and to determine the existence of statistically significant relationships with the dependent variable - learning outcome.

1.1. Course design

Course Design is part of the formal role of the instructor, which represents the rigidity or flexibility of the goal of education, teaching strategy, and assessment methods (Kim et al., 2021). It also describes the range in which the program can cover and respond to all student requests. The basic categories that describe and can improve course design are: course overview and introduction, learning objectives, assessment and measurement, and instructional materials.

It has been shown that course design has a substantial influence on students' satisfaction (Eom & Ashill, 2016), student's participation (Kornpitack & Sawmong, 2022), and that course design significantly influences learning, both in traditional and online settings (Lee, 2014). Furthermore, it has been found that course design significantly affects perceived usefulness, perceived ease of use and quality of e-learning, and perceived usefulness and quality of e-learning are the main drivers of student satisfaction (Nedeljković & Rejman - Petrović, 2022).

Therefore, in this study we hypothesize:

H1: Couse design is positively associated with Learning Outcomes.

1.2. Student Motivation

Change of the learning environment from face-to-face to distance teaching puts more responsibility on students to organize their time better and to self-motivate (Stevens, Bienz, Wali, Condie & Schismenos, 2021), as they transition from the role of passive to active learners. Self-motivation is a psychological construct and can be defined as the summoning of willpower that directs behaviour towards a specific goal (Zimmerman & Martinez-Pons, 1992). It has been shown that numerous student characteristics have a significant effect on satisfaction and learning outcomes (Bitzer & Janson, 2014). Some of those are: previous experience with distance learning, experience with using computers, self-efficacy, learning style, motivation, metacognition, and learning engagement (Prins, Veenman & Elshout, 2006). In this paper we focus on: motivation, self-regulated learning including metacognition, and learning engagement. Self-motivation could be defined as intrinsic, a psychological characteristic that causes an individual to carry out activities that will lead to personal satisfaction. On the other hand, extrinsic motivation represents a psychological characteristic which causes an individual to undertake activities that will enable him to achieve a separable outcome such as a reward, or recognition. These two types of motivation are also two measuring instruments that are suitable for explaining self-motivation (Schoor & Bannert, 2011). Following the controlled-to-autonomous continuum, three motivational profiles emerged: impersonal - amotivation, controlled - introjected and external regulation, and autonomous motivation - intrinsic, integrated, and identified regulation (Wei, Saab & Admiraal, 2023).

Based on the above review of potential students' motivation in online learning setting, the following hypothesis was formulated:

H2: Student Motivation is positively associated with Learning Outcomes.

1.3. Student self-regulation

The basic premise of the constructivist school of learning is that the most efficient learning happens when things are discovered at a time and pace that suits each individual. It is clear that students who are self-regulated and independent will achieve better success in an online learning environment. Students who are self-regulated are said to be "metacognitively, motivationally, and behaviorally active participants in their own learning process" (Zimmerman, 2008). This type of students take the initiative for the start and pace of their studies, coordinate their involvement and do not wait for lecturers, parents, or any other agents to initiate and guide them.

Self-regulated learning (SLR) implies planning, monitoring and adapting one's thoughts, feelings and actions in a cyclical process to attain a personal goal (Zimmerman, 2000) and it is one of crucial presumptions for the success in an online learning environment (Pelikan et al., 2021). Metacognitive processes involve learners' ability to plan, schedule, and evaluate their learning progress. Motivational processes indicate that the learners are self-motivated and willing to take responsibility for their successes or failures (Kuo, Walker, Belland & Schroder, 2013).

Information processing approach (Winne & Hadwin, 1998) portrays self-regulated learning as a model of three processes, namely: forethought, performance, and self-reflection according to Zimmerman (2000). Based on previous work on self-regulated learning, Green & Azevedo (2007) conclude that there is no typical cycle, most learning involves recycling through the cognitive architecture until a clear definition of the task has been created (Phase 1), followed by the production of learning goals and the best plan to meet them (Phase 2), which leads to the enacting of strategies to begin learning (Phase 3). According to other scholars, there are six sub-scale constructs: self-evaluation and mood-adjustment - preparation phase, task-strategies and environment-structuring - implementation phase, and help-seeking and time-management - reflection phase (Martinez-Lopez, Yot, Tuovila & Perera-Rodríguez, 2017).

Previous research has suggested that the learning design and the application of SRL strategies determine the learning effectiveness in learning activities during the COVID-19 pandemic (Panadero, Jonsson & Botella, 2017; Panigrahi, Srivastava & Panigrahi, 2021), that SRL strategies play a critical role in assessing student learning in online learning environments (Atmojo, Muhtarom & Lukitoaji, 2020), and that teachers can enhance their students' self-regulation in online learning and assist them in being more focused in online learning (Yu, Hu & Chen, 2022). Thus e-learning stakeholders should introduce effective strategies to overcome the lack of students' self-regulated learning because students with low SRL level would experience difficulties in autonomous learning settings, they would become dissatisfied, view the e-learning system as not useful, and resist using it (Al-Adwan, Albelbisi, Hujran, Al-Rahmi & Alkhalifah, 2021).

Some studies have identified essential factors exerting a great influence on online learning outcomes as motivation and self-efficacy (Yang, Tsai, Kim, Cho & Laffey 2006; Chen & Hu, 2020; Vrieling-Teunter, Stijnen & Bastiaens, 2021). After elaborate analysis of the importance of self-regulation in learning, the following hypothesis was formulated:

H3: Student self-regulation is positively associated with learning outcomes.

1.4. Dialogue (instructor - student and student – student)

In the online student-centered learning, a teacher could provide individualized instruction based on teacher-student interactions and communication, where teacher feedback could improve students' learning outcomes and enhance their engagement. Remote feedback, together with a contextualized and situated approach, is considered essential in online learning (Yu, 2021).

Unlike face-to-face classes, which rely on lectures as the basic learning method, collaboration assumes that knowledge is constructed socially via shared understanding groups through different knowledge discovery models such as: social collaborative learning, interactive, and discovery learning. The term dialogue is used to describe substantive, constructive, and meaningful interaction valued by each group participant. Dialogue promotes learning through active participation and enables deep cognitive engagement with the goal of developing higher level knowledge (Saghafian & O'Neill, 2018).

Education is characterized by interaction between instructor, student and content, and many studies have emphasized its importance in enhancing effectiveness in online education (Burnett, Bonnici, Miksa & Kim 2007; Yunusa & Umar, 2021). However, Kornpitack and Sawmong (2022) observed that many courses were being conducted online without the aid and assistance of a learning management system that would enable interaction of learners with their classmates, teachers, and assignments.

Three different types of interaction could be classified as: learner-content interaction, learner-instructor interaction, and learner-learner interaction (Bernard et al., 2009). Learner-content interaction refers to students' access to the materials that they are supposed to study (textbooks, course readings, lecture notes, audio-video materials). It is identical in traditional and online education, but instructor-student interaction and student-student interaction (dialogue) differ significantly. Kuo et al. (2013) found that student-content interaction was the strongest predictor of student satisfaction, and instructor-student interaction followed as the second strongest predictor that significantly contributed to student satisfaction.

Two hypotheses were formulated in regards to dialogue:

H4: Instructor-student dialogue is positively associated with learning outcomes, and

H5: Student-student dialogue is positively associated with learning outcomes.

The research hypotheses are graphically represented by the model shown in Figure 1.

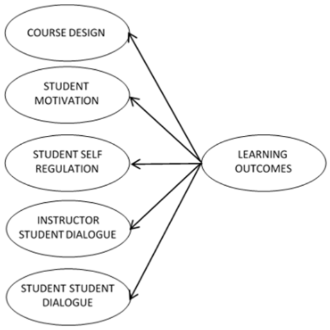

Figure 1 The research model
Source: the authors' research

2. Research methodology

For this research, we used a survey instrument that was developed and applied in (Eom & Ashill 2016). The instrument is based on the commonly administered IDEA (Individual Development and Educational Assessment) student rating system from Kansas State University, and the Motivated Strategies for Learning Questionnaire (MSLQ) authored by Pintrich, Smith, Garcia and McKeachie in 1993. The instrument itself was tested for suitability in Serbia (Petrov, Drašković, Uzelac & Ćelić, 2022) and proved adequate.

The instrument consists of seven parts. The first includes general information about the respondents, such as: age, gender, faculty, types of study, level of study, and experience in distance learning. The following blocks of questions (statements) are devoted to constructs: Course Design; Student Motivation; Self-Regulation; Student-Student Dialogue; Instructor-Student Dialogue; and Learning Outcomes.

Respondents rated their degree of (dis)agreement with the statements on a five-point Likert scale. To analyse the data collected via the questionnaires, we used IBM SPSS Statistics 25.0 statistical software for descriptive statistics on the data from the first part of the questionnaire (demographic characteristics of the respondents). SmartPLS 4.0 software was used for graphical approach to modelling structural equations using the least squares technique on the basis of variance (PLS-SEM), and for the analysis of the respondents' answers from the second part of the questionnaire, dedicated to examining the importance of factors influencing learning outcomes.

2.1. Demographics of the sample

Data was collected during the regime of online teaching in Serbia. Multiple methods of communication with students were used. Majority of students were contacted via previously formed teams on the MS Teams learning platform, but also via a database of student contacts on the Moodle platform.

Table 1 Demographics of the sample

		N of participants	% of participants
Gender			
	Male	131	36.4
	Female	229	63.6
Age			
	18-22	306	85.0
	23-26	32	8.9
	27-34	16	4.4
	35-44	6	1.7
Faculty			
	Faculty of Technical Sciences	213	59.2
	Faculty of Economics	147	40.8
Type of education			
	Vocational	35	9.7
	Academic	325	90.3
Academic programme			
	Bachelor	330	91.7
	Master	30	8.3
Experience in attending online classes			
	None	4	1.1
	Insufficient	75	20.8
	Sufficient	281	78.1
Total sample size (n) = 360			

Source: the authors

In total, over 2,500 students of the University of Novi Sad who were enrolled at the Faculty of Technical Sciences in Novi Sad and the Faculty of Economics in Subotica were contacted.

A total of 360 valid and complete questionnaires were collected during the one-month student survey. Response rate was around 14%, which is acceptable for this type of survey. Table 1 portrays demographic profile of the students.

Of the total number of respondents, 306 (85%) were between 18 and 22 years of age, 32 (8.9%) were between 23 and 26 years of age, 16 (4.4%) respondents were between 27 and 34 years of age, and 6 of them (1.7%) were between 35 and 44 years of age. When it comes to the gender of the respondents, 131 (36.4%) of them were male, and 229 (63.6%) were female.

In regard to academic program, the predominant number of respondents, 330 of them (91.7%), were from undergraduate/bachelor programs, while 30 of them (8.3%) were from master programs.

In terms of the faculty at which they studied, 213 (59.2%) of them were from the Faculty of Technical Sciences, while 147 (40.8%) were from the Faculty of Economics. Additionally, 35 (9.7%) of them were enrolled in vocational studies, while 325 (90.3%) were enrolled in academic studies.

The last demographic characteristic concerns the experience in attending online classes; 4 (1.1%) of the respondents said that they had no experience in attending online classes, 75 (20.89%) had insufficient, and 281 (78.1%) respondents said that they had enough experience in attending online classes.

2.2. Applied methods

All theoretical concepts used in this research have been taken from previous studies published in the scientific literature and they provide a theoretical, rational framework for this research.

The instrument was applied to a sample of 360 respondents using the structural equation model-based PLS methodology for two reasons. The first is that PLS is suitable for application in the early stages of theory development and testing. The more significant reason is that it is particularly suitable for analysing respondents' attitudes.

Latent variables, such as: attitudes, emotions, personality, motivation and the like, represent phenomena whose existence is concluded on the basis of observed behaviour. In this research, the respondents' attitudes were evaluated with a five-point Likert scale, and viewed as latent variables. Numerous authors have evaluated latent variables, i.e. examined complex interdependencies of latent constructs, with the aid of the statistical-econometric technique of structural equation modelling (SEM). SEM enables the modelling of the influence paths of latent constructs, i.e. variables that cannot be observed or directly measured.

Since latent constructs lack direct observations, they are operationalized, i.e. approximately measured using indicators that are called measurable, or manifest variables. For research conducted using questionnaires, each question in the questionnaire represents a measurable, manifest indicator. The parts of the structural equation model are: the structural model (in which the relations of latent constructs are defined) and the measurement model (which connects the latent constructs with their measurement indicators). Two types of techniques (methods) can be applied when modelling structural equations: covariance-based techniques (CB-SEM), and partial least squares techniques based on variance (PLS-SEM).

Although both techniques have the same roots, Hair, Sarstedt, Ringle and Mena (2012) state that the covariance structural equation modelling (CB-SEM) approach is considered particularly useful when conducting theory testing. On the other hand, variance-based structural equation modelling (PLS-SEM) approach is considered a 'soft' modelling approach to be applied in predictive studies when proven theory does not exist, or when theoretical assumptions and methods of measurement are insufficiently developed. PLS-SEM technique maximizes the explained variance of the endogenous latent variables by estimating the partial relationships of the model in an iterative series of Ordinary Least Squares (OLS) regression. To summarize, PLS-SEM emphasizes prediction while relaxing data requirements and specifying relationships.

3. Results and discussion

Structural equation modelling using variance-based least squares technique (PLS-SEM) can be used to estimate parameters in hierarchical latent variable models. Testing of the reflective-reflective hierarchical latent model used in the study was conducted according to the recommendations of Hair et al. (2012) along with requirements regarding data and model characteristics.

In accordance with the criteria for evaluating the results of reflective models, and in accordance with the fact that the research used a reflective-reflective hierarchical latent model and within it the approach of repeating indicators, the constructs of all three hierarchical levels were tested by measuring: indicator reliability, internal consistency, convergent validity, and discriminant validity of latent constructs.

The composite reliability of the group of indicators which measure the construct is based on the Composite Reliability (CR) and Average Variance Extracted (AVE). Internal consistency was confirmed in all constructs measured by both indicators. If we take into account the Composite Reliability indicator, which represents the internal consistency of the test, i.e. the degree to which all test subjects covary with each other, with a limit of 0.7 as acceptable in Table 2, it is noticeable that for each construct the value of this indicator is in the range of 0.81 to 0.96.

The application of this indicator is more frequent for Confirmatory Factor Analysis (CFA), unlike the indicator Crombach's Alpha, which is more suitable for Exploratory Factor Analysis (EFA). Average Variance Extracted is in the interval from 0.631 to 0.864, which is considered acceptable, that is, more variance is covered by the construct than by measurement error.

Table 2 Reliability validation of the model

Construct	Factor Loading	α	CR	AVE	VIF
Course Design	0.816***	0.864	0.880	0.647	2.566
	0.857***				2.769
	0.825***				1.881
	0.773***				1.706
	0.747***				1.713
Instructor Student Dialogue	0.893***	0.901	0.935	0.769	0.891
	0.913***				0.91
	0.908***				0.901
	0.789***				0.807
Student Student Dialogue	0.705***	0.814	0.947	0.612	2.044
	0.788***				2.591
	0.843***				1.439
	0.835***				2.081
Student Self-Regulation	0.807***	0.813	0.868	0.631	1.778
	0.760***				1.792
	0.774***				1.767
	0.833***				1.485
Student Motivation	0.704***	0.719	0.748	0.526	1.846
	0.853***				1.480
	0.702***				1.162
Learning Outcomes	0.743***	0.921	0.927	0.864	2.024
	0.933***				3.394
	0.941***				3.912
	0.914***				3.127

Source: the authors

During the analysis, the indicator of multicollinearity embodied in the variance inflation factor (VIF) was also taken into account. As the VIF values are below 5, it can be considered that the observed independent variable is not highly correlated with another independent variable. The results are shown in Table 2.

After testing the internal consistency and convergent validity of the constructs, an examination of the uniqueness of each latent construct in relation to other latent constructs in the structural, hierarchical model follows, by testing the discriminant validity of the latent constructs. Discriminant validity was tested with the use of the Fornell-Larcker criterion (Hair et al., 2012). Table 3 presents results of the examination of the discriminant validity of the mentioned constructs in this way.

Table 3 Discriminant validity Heterotrait Monotrait Ratio HTMT

	CD	ISD	SM	SSR	SSD
CD					
ISD	0.747				
SM	0.704	0.575			
SSR	0.704	0.517	0.791		
SSD	0.713	0.816	0.505	0.473	
LO	0.584	0.534	0.309	0.196	0.670

Source: the authors

Since the square root of the average value of the extracted variance (AVE) of each construct is greater than all the correlations of each construct with other constructs in the model, the discriminant validity of them can be confirmed. In other words, all constructs in the model can be viewed as separate entities, i.e. they should not be regrouped and/or merged with each other.

The causal relationship of the hypotheses was tested examining the structural model using Smart PLS software.

Table 4 Hypotheses confirmation for dependent variable Learning Outcomes

Path	Path coefficient	Hypothesis
H1: Course Design	0.525***	supported
H2: Student Motivation	0.286***	supported
H3: Student Self - Regulation	0.172***	supported
H4: Instructor Student Dialogue	0.496***	supported
H5: Student Student Dialogue	0.721***	Supported

Note: *** significant at $p \leq 0.001$

Source: the authors

The statistical significance of the hypothesized relationships was examined by bootstrapping procedure. The t-test for the standardized path coefficients and for calculated p values were verified based on a two-tailed test with significance levels of 0.01 and 0.05.

Our results suggest the presence of a significant positive relationship between chosen constructs and dependent variable Learning Outcomes.

To test our hypothesis we utilized partial least square-based structural equation modelling using SmartPLS software. A hierarchical latent variable model using reflective-formative type was used, as suggested by Becker, Klein and Wetzels (2012).

Based on the analysis, the evidence was obtained suggesting that Learning Outcomes among students at University of Novi Sad could be explained by a second-order hierarchical model which is reflected by Course Design, Student Self-

Regulation and Student-Student Dialogue, as is presented in Figure 2.

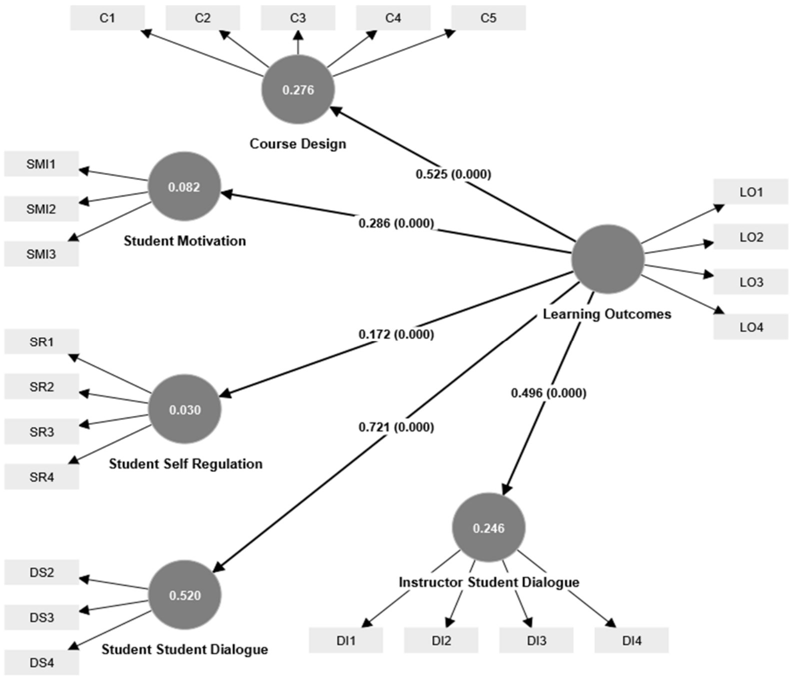

Figure 2 The research model - results
Source: the authors

Conclusion

The results of the presented research are important from the aspect of contributing to the literature dedicated to identifying the key success factors of online learning. Additional contribution refers to the research conducted in Republic of Serbia, i.e. at the University of Novi Sad. The statistical analysis led to the revised measurement model, whose results provided support for the reliability and convergent and discriminant validities of the measures used in the study.

The results of this study have significant implications for lecturers. It is clear that the role of the lecturer through course design is the cornerstone of the university online education. Improving the skills and knowledge of lecturers in the areas of: course structure preparation, discussions and interactions, technological solutions for collaboration during lectures or other types of student engagement, as well as motivation methods; would significantly affect the target variable learning outcomes.

One area for further research remains a more detailed analysis of the model itself and the possibility of finding the interdependence of constructs that affect perceived learning outcomes and user satisfaction.

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