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PAPER

Kosovo Students' Readiness for Online Learning during the Covid-19 Pandemic

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ABSTRACT

Online learning is one of the main alternatives to traditional classroom learning during the COVID-19 pandemic and the new regular periods. Online learning has been used at many educational levels on a range of platforms. Numerous studies have shown that online education is beneficial across all academic levels and topic areas. This study aims to assess students' preparedness for online learning during the COVID-19 epidemic at higher education institutions. A quantitative strategy built on a survey method was employed for this research project. Students from higher education institutes in Kosovo were purposefully chosen as the study group. One thousand five hundred people were selected as a sample from the target population. The simple-to-use structural equation modeling (SEM) model was utilized to examine the data in this paper. This methodology assesses how prepared students from Kosovo are for online learning. Self-directed learning (SDL), learner control, learner motivation, and online communication self-efficacy were the five components of that scale. The study confirmed that because they were driven to learn in this e-learning environment, students at higher education institutions (HEIs) were considerably more personalized and successful in their decisions about their online educational lives during the COVID-19 pandemic.

KEYWORDS

COVID-19, higher education institutions (HEIs), online learning, simple-to-use structural equation modeling (SEM) model

1 INTRODUCTION

At the national and worldwide levels, the COVID-19 pandemic issue has had an immediate impact on education that was hitherto unforeseen [1] [2]. The educational system has changed as a result of COVID-19, including in terms of the curriculum, educator duties, student roles, and evaluation procedures [3]. Additionally, COVID-19 has changed how future generations will learn and even how people will view teachers [4] [5]. Sipayung and Wibawa [6] claim that COVID-19 was the catalyst for three significant changes in the field of education. Examples of this include techniques for

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educating individuals, cutting-edge educational approaches that might lead to the most significant discoveries, and the digital divide that influences changes in education.

COVID-19 also stresses the importance of acquiring future-ready life skills and boosting the use of technology in school [7] [8]. Regarding schooling in the COVID-19 pandemic setting, digital technology and instructional innovation are two key ideas. To counteract COVID-19's effects on education, particularly learning, many countries have put policies in place. Distance learning, especially online learning or e-learning, is the most popular method of learning mitigation. One of the key problems is how students are prepared for online or e-learning [9]. To build a comprehensive assessment of students' readiness for online learning, numerous investigations must be done. The goal of this study was to uncover more thorough online learning preparation techniques.

In response to the pandemic, distant learning, and the fast growth and use of the Internet, online education has rapidly increased [10] [11]. E-learning uses technology to enhance the teaching and learning process [12–14]. E-learning's goals are to cut costs, increase accessibility, and increase production [15]. E-learning, according to Maatuk et al. [16], is the electronic delivery of instructional materials or educational experiences through a multimedia computer. Alqahtani and Rajkhan [17] claim that e-learning is a distinct kind of instructional system. Electronic technology-based learning is defined by Rahmani et al. [18] as learning that takes place online or through a computer. Utilizing e-learning has several advantages, including speeding up learning, being more economical, enabling student involvement with the material, and being always available [19] [20]. According to Al Rawashdeh et al. [21], there are six primary components to the benefits of e-learning systems: connectivity, global information access, adaptability, interactivity, collaboration, and extended opportunities for e-content, autonomous and immediate learning assessment. The remaining factors are flexibility, interactivity, collaboration, and the use of discussion tools to support collaborative learning outside of the classroom. E-learning advantages increase lifelong learning opportunities for everyone while also enhancing self-directed learning (SDL) and educational effectiveness [22–24].

1.1 Objective of the study

The objective of the study is to investigate the readiness of Kosovo students for online learning during the COVID-19 pandemic using higher education institutions (HEIs) in Kosovo. The key questions addressed in this study are as follows:

Q1: Were students willing to learn remotely during the COVID-19 pandemic?
Q1a: What is self-efficacy in using online platforms for e-learning?
Q1b: How well are the learning objectives achieved through e-learning?
Q1c: Do students have self-control during the online learning process?
Q1e: How motivated were the students for online learning?
Q1f: Were students safe when communicating online?

2 LITERATURE REVIEW

McVay developed a 13-item scale to measure students' readiness for online learning [25]. Another important factor affecting students' online learning readiness (OLR) was their ability to manage their time. Hung et al. [26] created a comprehensive scale to assess students' readiness for online learning in 2010. The scale has five dimensions and covers all aspects of OLR: 1) Computer/Internet self-efficacy, 2) SDL, 3) Learner control, 4) Motivation for learning, and 5) Self-efficacy in online communication. The OLR conceptual model was built with the dimensions discussed in the following subsections.

2.1 Computer & internet self-efficacy

Since online networks are used to deliver online learning, it is crucial to understand how students view ICTs and gauge their proficiency in using them for online learning. According to a 10-item questionnaire developed by Compeau and Higgins [27], computer self-efficacy significantly affects computer use outcomes, the emotional responses of computer users, and actual computer use. Additionally Jpepa [28] found that pupils with higher Internet self-efficiency performed and learned more effectively than those with lower levels of Internet e-learning. Accordingly, several scales have been created to assess people's self-efficacy with computers and the Internet.

2.2 Self-directed learning

Self-directed learning is the process of identifying one's learning needs and establishing learning objectives. Garrison, cited by Rafique et al. [29], developed a comprehensive model of SDL and defined it as "an approach that helps stimulate students' assumption of personal responsibility." Lin and Hsieh [30] contended that successful online students made their own decisions to meet their needs.

2.3 Learner control

Alongside the rapid advancement of ICTs, the idea of learner control has also developed. Content, order, and pace of learning are all under the students' control [31]. According to Shute and Towle [32], students should have complete discretion over the order of educational materials to develop their decision-making skills. Learner control affects student task performance in a web-based learning environment.

2.4 Learning motivation

Motivation significantly affects students' attitudes and behaviors toward learning in any educational situation. Intrinsic motivation plays a vital role in aiding students' cognitive, physical, and social growth. On the other hand, extrinsic motivation is linked to achieving incentives such as stellar academic performance, honors, and prizes.

2.5 Online communication self-efficacy

Students must use computer-mediated tools to complete educational tasks. Students who are shy or hesitant perform better in online learning environments. Online communication self-efficacy is required for students to overcome communication limitations and avoid isolation during online learning [26].

2.6 Students' readiness for online learning during the COVID-19 pandemic

Tang et al. [33] looked into a number of significant factors in the research framework linked to learning preparedness, learning motivation, and student self-efficacy during the coronavirus outbreak. The fictitious model was approved using confirmatory factor analysis. The results showed no statistically significant distinctions between males and females. The posthoc test revealed that the PG students' mean results were greater than those of the UG and SD students.

During the COVID-19 pandemic, Sahoo [34] conducted a study to assess student teachers' e-readiness and perceptions of online learning. The study revealed that only 35% of student teachers are digitally proficient, and the majority believe that online classes lack proper teacher-student and student-student interactions. Sahoo [34] concludes by emphasizing the importance of government, parents, institutions, and teacher support in making online learning more accessible and effective. Churiyah et al. [35] investigated the implementation of distance learning systems in Indonesian education during the COVID-19 pandemic. The investigation highlighted that Indonesia has a virtual infrastructure, but understanding instructors and schools is still crucial. Students who struggle with learning self-regulation find it challenging to manage their remote learning activities. The study involved in-depth interviews with samples of kids, teachers, and parents from both rural and urban areas of Indonesia that were most affected by the COVID-19 virus. It included literature research from various reports and scientific journals. Rafique et al. [29] designed a study to determine Library and Information Sciences (LIS) and Information Management (IM) students perceived OLR during the COVID-19 pandemic. The results indicated that LIS students' choices for their online learning activities were not entirely successful and individualized. However, they were inspired to study through online learning and felt comfortable using the Internet and computers in general. Additionally, the study found that respondents' grade and age were excellent indicators of their online learning readiness.

During the COVID-19 pandemic, Adams et al. [36] investigated students' readiness for e-learning. The pupils' level of preparation was evaluated using descriptive and inferential statistics, along with the differential item functioning (DIF) exam. The validity and reliability of the research instrument were assessed with the aid of the WINSTEPS Rasch model assessment program. The results show that the majority of students were ready for an education style that involved e-learning. In Nigeria during the COVID-19 outbreak, Olayemi et al.'s [37] investigation explored students' attitudes toward and preparation for online learning. This study employed a descriptive survey research methodology, with a structured questionnaire serving as the primary data gathering tool. The questionnaire was completed by (148) undergraduate students in total. The data were analyzed using tables, frequency counts, charts, and percentages. On the positive side, the study found that most respondents asserted to be knowledgeable. Furthermore, the findings revealed that the majority of respondents possessed the advanced ICT skills and competencies required for online learning. However, the study also identified several perceived challenges to effective online learning, including high data costs, poor Internet services, erratic power supply, inaccessibility to online library resources, and limited computer access.

3 METHODOLOGY

3.1 Participants

We purposefully chose the students at HEI in Kosovo as our analysis's unit of analysis. 1500 people were selected as a sample from the target population.

3.2 Data collection instrument

For this research project, a quantitative strategy built on a survey method was employed. The scale used to collect data was adapted from a study by Rafique et al. [29] and slightly altered to account for the pandemic condition. This data collection tool included 21 questions that covered five aspects of students' readiness for online learning: computer/internet self-efficacy (4 questions), self-directed learning (5 questions), learner control (4 questions), motivation for learning (4 questions), and online communication self-efficacy (4 questions). The questionnaire included demographic data about the respondents, including their gender, age, faculty, and degree of education.

3.3 Data analysis

Stata, a simple-to-use structural equation modeling (SEM) application that examines correlations between observable and latent (unobserved) variables, was used to analyze the data from the survey. Using Stata, the quantitative data collected from the questionnaire was described, tested, and analyzed. Descriptive statistics will be summarized and projected in suitable graphs such as tables, pie charts, bar charts, etc., to make them more readable and easily understood. Stata software was used to run structural equation modeling.

Structural equation modeling. This is a multivariate statistical framework that is used to model complex relationships between directly observed and indirectly observed (latent) variables. A number of statistical techniques are used in SEM, sometimes referred to as the study of covariance structures or causal modeling, to explore complex interactions between one or more independent variables and one or more dependent variables. By applying SEM and route analysis with the maximum likelihood estimate technique, the research hypotheses were put to the test. It has been discovered that this method produces trustworthy results even in situations where the data may not conform to SEM's presumptions, such as a normal distribution and a sizable sample size. For model specification in SEM, a path diagram is used, and the parameter estimates are shown graphically on the path diagram. There are two models used in the path analysis:

- The structural model shows the connections (paths) between the relevant constructs.
- The measurement models show the linkages (paths) between the relevant constructs in the structural model.

In order to maximize the variance in the dependent variables that can be explained, SEM focuses on the prediction of a certain set of hypothesized relationships [38]. The model will be evaluated using item loadings, reliability coefficients (composite reliability), convergent and discriminant validity, and more. It will be deemed sufficient when an individual item load exceeds 0.7 [39]. An appropriate reliability estimate is one with a composite reliability score of 0.7 or above, which is equivalent to Cronbach's alpha for internal consistency [39]. To support the use of each construct, the average variance extracted (AVE) will be calculated to measure the variance collected by the indicators relative to measurement error.

When values exceed 0.50, a construct will continue to be used [40]. The degree to which items distinguish between constructs or measure distinct concepts—the discriminant validity of the measures—will be evaluated by looking at the correlations between possibly overlapping constructs [40]. The average variance shared between each construct and its measures is anticipated to be bigger than the variance shared between the construct and other constructs [40]. Items are anticipated to load on their constructs in the model more strongly. The path coefficients (standardized betas) will be examined in order to evaluate the structural model. In order to evaluate the relevance of these path coefficients, T statistics will also be computed. The proposed model's overall predictive power and usefulness will also be assessed using R 2.

SEM includes two types of factor analysis. Exploratory factor analysis (EFA) and confirmatory factor analyses (CFA) are two forms of factor analysis used in SEM. EFA is used to determine the structure of a collection of a set of data, especially during the initial stages of developing an instrument, to evaluate concept validity. On the other hand, CFA is employed to validate hypotheses related to latent and unobserved variables [38]. CFA was used to validate the latent component structure during the SEM analysis. Following the methodology recommended by Jöreskog and Moustaki [41], the confirmatory analysis of the CAAS, Employee Engagement, and Organizational Performance used the one-factor congeneric model.

The one-factor congeneric model enables the reduction of multiple observable variables to a single composite scale that takes into consideration the distinctive contribution of each item. A group of observed indicator variables is regressed on a single latent variable using the one-factor congeneric model. Following is a regression analysis done on the indicated latent construct using each of the scales below and their related indicator variables:

- 4-items CSE scale = Computer self-efficacy
- 5-item- SDL = Self-directed learning
- 4-item LC = Learner Control
- 4-item LM = Learning motivation
- 4-item OSCE = Online communication self-efficacy

The rigorously confirmatory approach is the chosen strategy to test congeneric models [41]. This method focuses on accepting or rejecting a certain model, making it the most rigorous type of confirmatory test. In this approach, the researcher uses data to either support or refute a single priori measurement model which can be derived from a combination of theory and data, similar to the current study [41]. Stata was used to extract the covariance matrix and parameter estimates from the items within each a priori dimension. The maximum likelihood approach was then employed to evaluate the model fit and analyze each congeneric model [41].

Model fit. The model fit was estimated using the Comparative Fit Index (CFI) and the Incremental Fit Index (IFI) [42]. When dealing with a modest sample size, the CFI is the preferred index for assessing model fit [42]. The IFI was created to address the problem of a small sample size. The widespread consensus is that CFI and IFI values greater than 0.9 indicate a satisfactory model fit [42].

4 RESULTS

4.1 Descriptive statistics

A total of 1500 participants took part in the survey. Respondents were given a period to complete the questionnaire. At the end of this period, 1272 respondents had completed the survey, which equates to a response rate of 85%.

Gender of respondents. Gender is one of the demographics collected in this study. As shown in Figure 1, females made up much of the study sample. There were 750 (58.96%) female respondents compared to 522 (41.04%) male respondents.

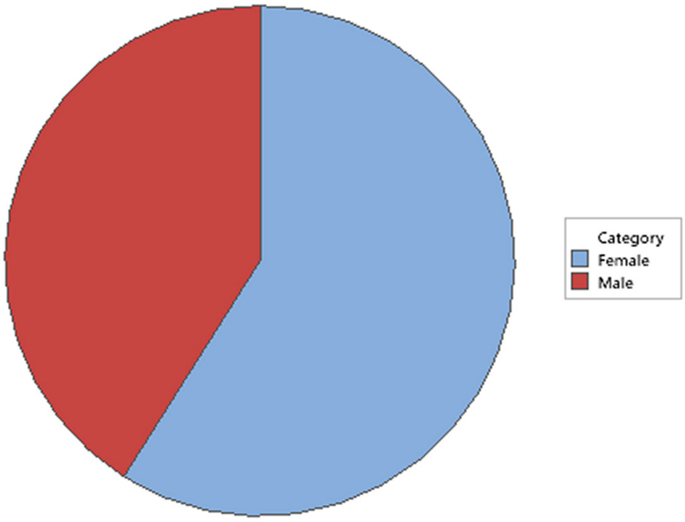

Fig. 1. Gender profile of study participants

It can be inferred from this percentage of participation that there are a significant number of female students in HEIs in Kosovo.

Age of respondents. The age groups of the participants are presented in Figure 2. The respondents ranged from those in their late teenage years to those aged 55. The majority of the students that responded are 18 years of age, closely followed by students who are 20 years of age. Students between the ages of 43 and 55 gave the least response.

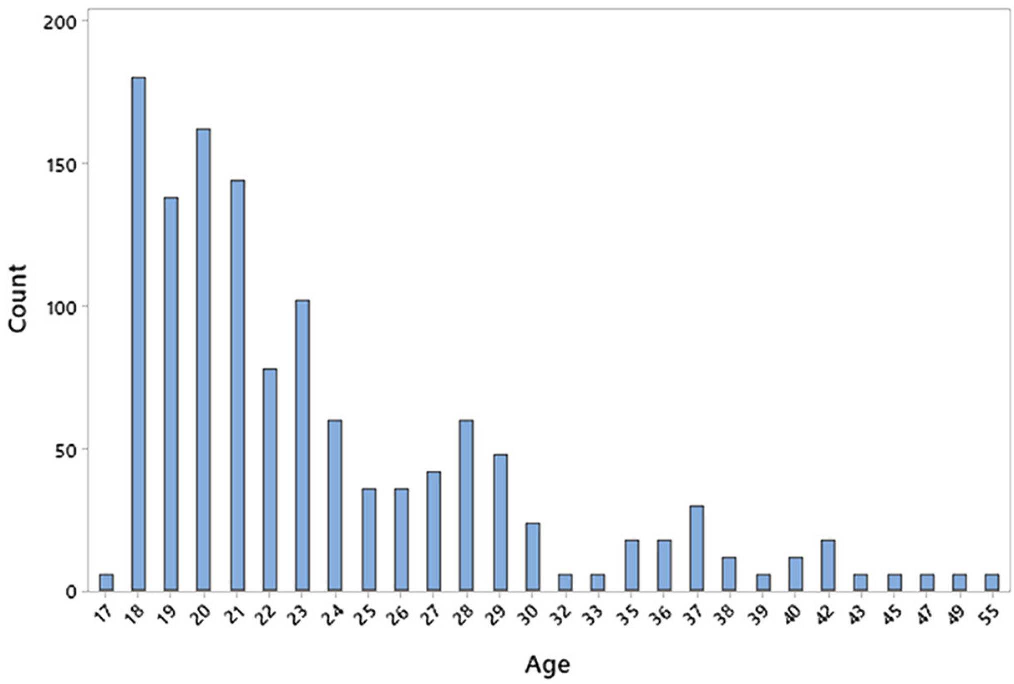

Fig. 2. Age of respondents

It can be inferred that the majority of the respondents are young students who have a niche for online learning using different tools.

Faculty of respondents. In response to the question on the faculty of participants, many (79.25%) of the participants were in the Economy faculty, while 264 (20.75) were in the Sport faculty. The presentation of the faculty of participants is shown in Figure 3.

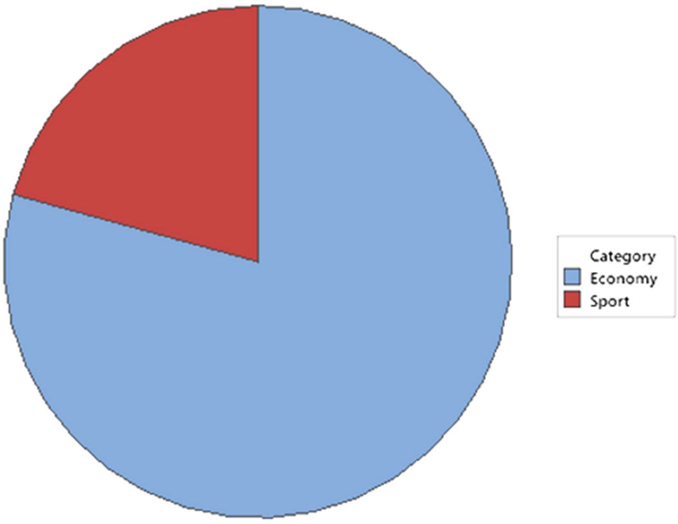

Fig. 3. Faculty

Level of study. Out of 1272 respondents, 918 (72.17%) are studying for their Bachelor's degree, while 354 (27.83%) are studying for a Master's degree (see Figure 4).

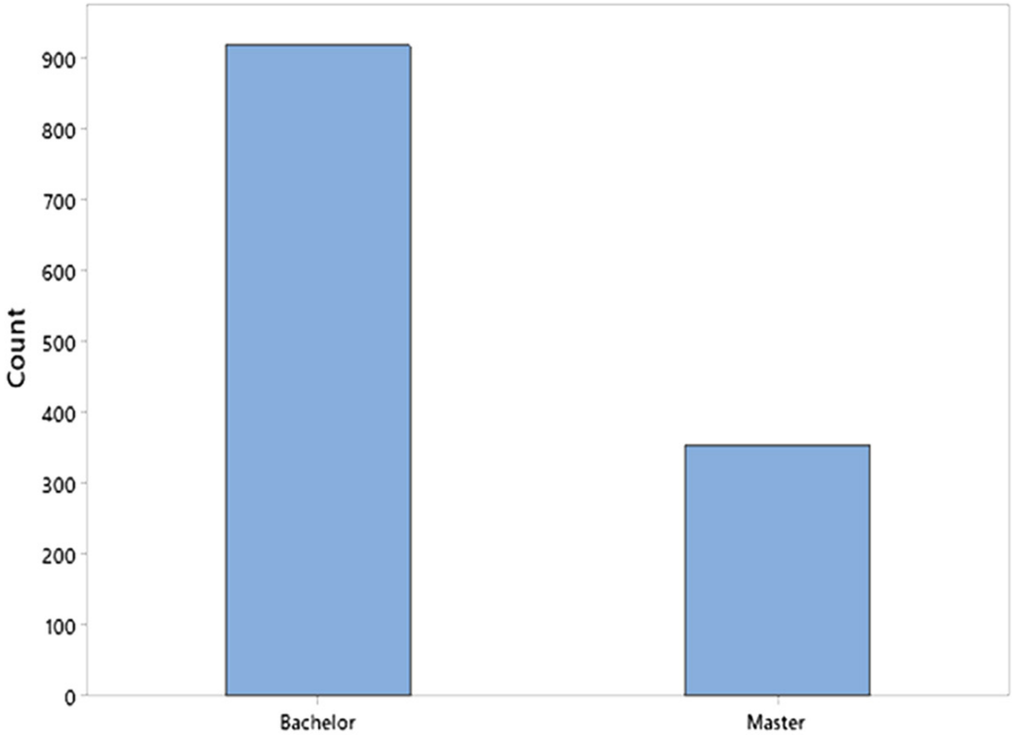

Fig. 4. Level of study

4.2 The reliability of the measures

To assess the internal consistency and reliability of the 21 scale items, the Cronbach's alpha value was determined. The alpha value was discovered to be 0.837, which showed excellent consistency between the scale's numerous elements. Additionally, this result was higher than the suggested level of 0.70 [43].

4.3 Model testing results

This study used a pre-validated instrument for data collection, and to validate it, CFA was conducted using Stata. The study's hypothetical model was verified, and various fit indices was calculated, including chi-square/degree of freedom, CFI, Tucker-Lewis Index (TLI), RMSEA (Root Mean Square Error of Approximation), and Standardized Root Mean Square Residual (SRMR). Table 1 presents the cut-off criteria for these measurements. Based on the Brown's (2015) recommendations, the model fit indices were found to be within acceptable ranges (Table 2). The study model was deemed to be well-fitting; however three items—SDL1, SDL2, and LC2—had weak factor loading (< 0.50) (Figure 5). Nevertheless, all items were statistically significant overall, and each item on the scale was successfully loaded (> 0.50) under the latent dimension, according to the factor loading results [39].

Table 1. Cut-off criteria

Measure	Terrible	Acceptable	Excellent
CMIN/DF	> 5	> 3	> 1
CFI	< 0.90	< 0.95	> 0.95
SRMR	> 0.10	> 0.08	< 0.08
RMSEA	> 0.08	> 0.06	< 0.06
P Close	< 0.01	< 0.05	> 0.05

Table 2. Model fitness analysis summary

Measures of Fit	Estimates	Interpretation
Test statistic	61.671	
Degrees of freedom	43	
P-value (Chi-square)	0.032	
Model Test Baseline Model:		
Test statistic	347.081	
Degrees of freedom	55	
P-value	0.000	
User Model versus Baseline Model:		
Comparative Fit Index (CFI)	0.936	Excellent fit
Tucker-Lewis Index (TLI)	0.918	Excellent fit

(Continued)

Table 2. Model fitness analysis summary *(Continued)*

Measures of Fit	Estimates	Interpretation
Loglikelihood and Information Criteria:		
Loglikelihood user model (H0)	–2209.812	
Loglikelihood unrestricted model (H1)	–2178.977	
Akaike (AIC)	4465.624	
Bayesian (BIC)	4529.154	
Sample-size-adjusted Bayesian (BIC)	4456.448	
Root Mean Square Error of Approximation:		
RMSEA	0.061	
90 Percent confidence interval – lower	0.019	
90 Percent confidence interval – upper	0.093	
P-value RMSEA <= 0.05	0.284	
Standardized Root Mean Square Residual:		
SRMR	0.061	

4.4 Analysis of research questions

This section presents the findings derived from testing all six research questions. The result presented in this section illustrates the key findings for each question.

RQ1 – Were students willing to learn remotely during the COVID-19 pandemic?

Table 3. Perceived online learning readiness during COVID-19 (N = 1272)

	Statement	Mean	Std. Deviation	Factor Loading
CSE		**2.29**	**1.421**	
CSE1	I have good knowledge and ability to use online platforms for online learning	2.10	1.316	0.5
CSE2	I have sufficient knowledge and skills to use various programs to perform tasks such as Microsoft office, etc.	2.43	1.505	0.51
CSE3	I have sufficient knowledge of using google, yahoo, and other platforms for gathering information on the internet.	2.13	1.247	0.63
CSE4	I have enough knowledge to choose different problems that appear to me during online learning	2.51	1.616	0.65

(Continued)

Table 3. Perceived online learning readiness during COVID-19 (N = 1272) *(Continued)*

	Statement	Mean	Std. Deviation	Factor Loading
SDL		**2.59**	**1.594**	
SDL1	I have set online learning objectives	3.19	1.733	0.46
SDL2	I carry out my study plan	2.36	1.604	0.46
SDL3	I managed my time well while learning online	2.44	1.524	0.71
SDL4	I ask for help from the teachers for the problems that appear during online learning	2.40	1.513	0.61
SDL5	I have high expectations of my online learning performance	2.54	1.595	0.74
LC		**2.41**	**1.530**	
LC1	I can manage my learning progress	2.47	1.592	0.43
LC2	I am not distracted by other online activities when learning online (instant messaging, web surfing)	2.58	1.584	0.53
LC3	I redo online learning materials based on my needs.	2.15	1.417	0.61
LC4	I do not replace the time for learning with other activities	2.44	1.528	0.59
LM		**1.98**	**1.165**	
LM1	I am open to new ideas	1.96	1.153	0.73
LM2	I have the motivation to learn.	1.99	1.287	0.62
LM3	I get better from my mistakes.	1.76	.892	0.7
LM4	I like to share my ideas with others	2.19	1.327	0.59
OCSE		**2.39**	**1.502**	
OCSE1	I feel confident in using online tools (email, chat) to communicate effectively with others.	2.16	1.412	0.63
OCSE2	I feel confident in expressing myself (emotions and humor) through text.	2.53	1.522	0.73
OCSE3	I feel safe posting questions in online discussions.	2.37	1.511	0.74
OCSE4	I feel confident in sharing researched resources online	2.49	1.565	0.68

To assess the respondents' online learning readiness (OLR) during COVID-19, they were provided with a set of 21 items. Table 3 displays the participant responses for each item, along with their mean (M) and standard deviation (SD). Among the OLR dimension for students at HEIs, self-directed learning (SDL) emerged as the most crucial, with a mean score of 2.59 (1.594). Additionally, the study also revealed that students at HEIs demonstrated positive outcomes in various aspects of online learning, such as setting online learning objectives, having study plans, effective time management, seeking for help from teachers when facing challenges, and maintaining high expectations for online learning performance during COVID-19.

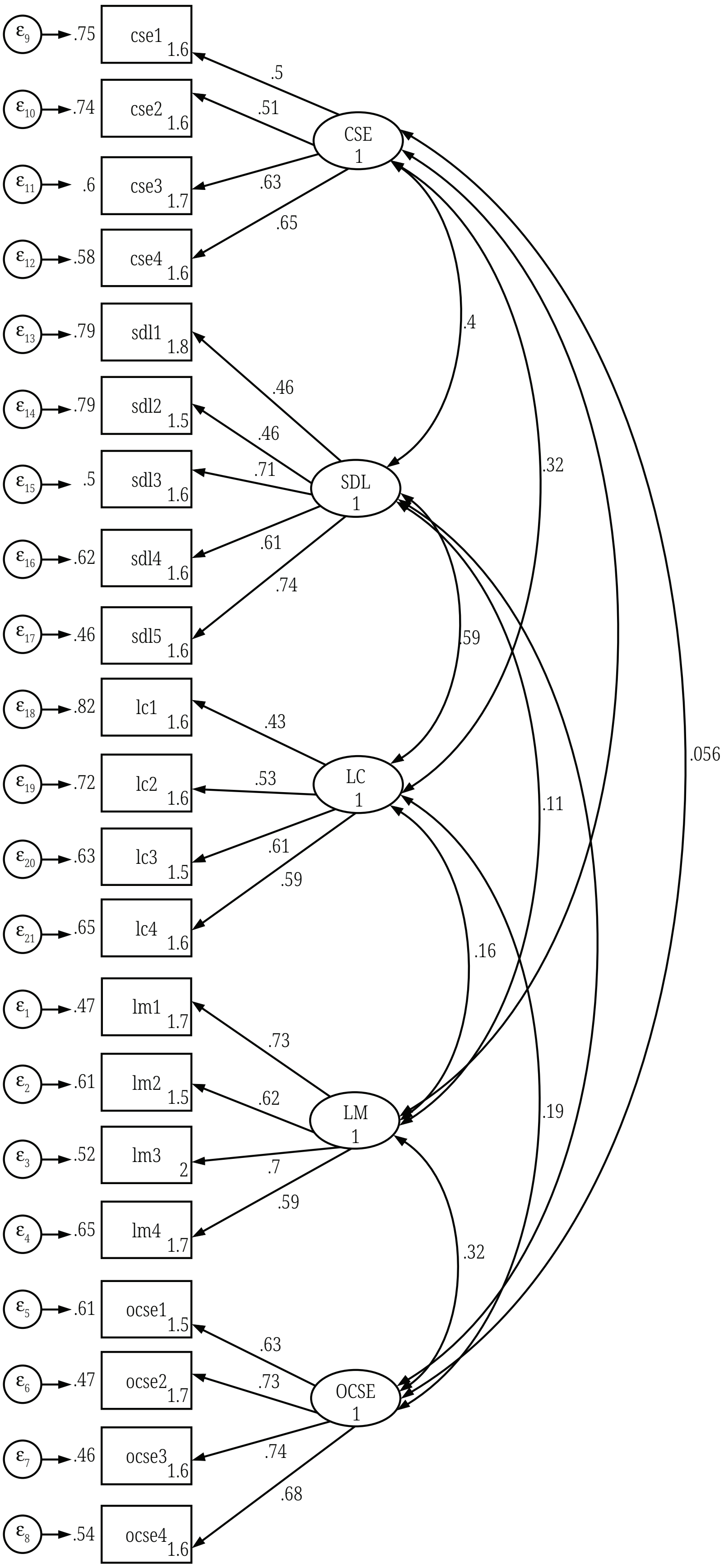

Fig. 5. Measurement model and factor loading

The second-ranked dimension was learner control (M = 2.41, SD = 1.530) followed by online communication self-efficacy (M = 2.39, SD = 1.502), and computer self-efficacy (M = 2.29, SD = 1.421). However, with a mean score of 1.98 (1.165), learning motivation continued to be the OLR dimension with the lowest ranking for students at HEIs. The findings indicated that learner control was supported by the vast majority of participants. They felt capable of managing their learning progress (M = 2.47, SD = 1.592). They could redo online learning materials based on their needs (M = 2.15, SD = 1.417) and they do not replace the time for learning with other activities (M = 2.44, SD = 1.528) (Table 3).

RQ2 – What is self-efficacy in using online platforms for e-learning?

A statistically significant and favorable effect was discovered in the path coefficient at the 0.001 level when examining the direct effect on the link between the measurement variable (CSE2) on the latent variable (CSE). Similarly, the route coefficient exhibits a statistically significant and favorable effect at the 0.001 level when examining the direct effect of the measurement variable (CSE3) on the latent variable (CSE). Additionally, a statistically significant and favorable effect was discovered in the path coefficient at the level of 0.001 when examining the direct influence of the measurement variable (CSE4) on the latent variable (CSE) (Table 4).

Table 4. The relationship between the measurement variable (CSE) on the latent variable (CSE)

Measurement	OIM					
	Coef.	Std. Err.	z	P > |z|	[95% Conf. Interval]	
cse1 <-						
CSE	1 (constrained)					
_cons	2.099057	.0368871	56.90	0.000	2.026759	2.171354
cse2 <-						
CSE	1.015946	.0845375	12.02	0.000	.8502558	1.181637
_cons	2.429245	.0421873	57.58	0.000	2.34656	2.511931
cse3 <-						
CSE	1.156538	.0876655	13.19	0.000	.9847169	1.328359
_cons	2.127358	.0349588	60.85	0.000	2.05884	2.195876
cse4 <-						
CSE	1.456277	.1133134	12.85	0.000	1.234187	1.678368
_cons	2.514151	.0452829	55.52	0.000	2.425398	2.602904

RQ3 – How well are the learning objectives achieved through e-learning?

A statistically significant and favorable effect was found in the path coefficient at the 0.001 level when examining the direct effect on the measurement variable (SDL2) on the latent variable (SDL). When examining the direct relationship between the measurement variable (SDL3) and the latent variable (SDL), a statistically significant and favorable effect is discovered in the path coefficient at the 0.001 level. When examining the direct association between the measurement variable (SDL4) and the latent variable (SDL), a statistically significant and favorable effect was discovered in the path coefficient at the 0.001 level. There is statistically a significant result when examining the direct impact of the measurement variable (SDL5) on the latent variable (SDL) (Table 5).

Table 5. The relationship between the measurement variable (SDL) on the latent variable (SDL)

Measurement	OIM					
	Coef.	Std. Err.	z	P >|z|	[95% Conf. Interval]	
sdl1 <-						
SDL	1 (constrained)					
_cons	3.188679	.0483242	65.99	0.000	3.093966	3.283393
sdl2 <-						
SDL	.930782	.0763224	12.20	0.000	.7811929	1.080371
_cons	2.358491	.0447047	52.76	0.000	2.270871	2.44611
sdl3 <-						
SDL	1.282123	.0900728	14.23	0.000	1.105584	1.458662
_cons	2.443396	.0422455	57.84	0.000	2.360597	2.526196
sdl4 <-						
SDL	1.400348	.097155	14.41	0.000	1.209927	1.590768
_cons	2.542453	.0441413	57.60	0.000	2.455938	2.628968

RQ4 – Do students have self-control during the online learning process?

The path coefficient shows a statistically significant and positive effect at the 0.001 level when examining the direct effect on the link between the measurement variable (LC2) and the latent variable (LC). When examining the direct association between the measurement variable (LC3) and the latent variable (LC), the path coefficient shows statistically significant and positive results at the 0.001 level. A statistically significant and positive effect was discovered in the path coefficient at the 0.001 level when examining the direct influence on the link between the measurement variable (LC4) and the latent variable (LC) (Table 6).

Table 6. The relationship between the measurement variable (LC) on the latent variable (LC)

Measurement	OIM					
	Coef.	Std. Err.	z	P >|z|	[95% Conf. Interval]	
lc1 <-						
LC	1 (constrained)					
_cons	2.471698	.0444751	55.57	0.000	2.384528	2.558868
lc2 <-						
LC	1.218371	.1066753	11.42	0.000	1.009292	1.427451
_cons	2.580189	.0441886	58.39	0.000	2.493581	2.666797
lc3 <-						
LC	1.262015	.1074989	11.74	0.000	1.051321	1.472709
_cons	2.150943	.0394517	54.52	0.000	2.073619	2.228267
lc4 <-						
LC	1.326088	.1214386	10.92	0.000	1.088072	1.564103
_cons	2.443396	.0425531	57.42	0.000	2.359994	2.526799

RQ5 – How motivated were the students for online learning?

The path coefficient shows a statistically significant and positive effect at the 0.001 level when examining the direct effect on the link between the measurement variable (LM2) and the latent variable (LM). When examining the direct association between the measurement variable (LM3) and the latent variable (LM), the path coefficient shows statistically significant and positive results at the 0.001 level. There is statistically a significant and positive effect at the 0.001 level discovered in the path coefficient when assessing the association between the measurement variable (LM4) and the latent variable (LM) (Table 7).

Table 7. The relationship between the measurement variable (LM) on the latent variable (LM)

Measurement	OIM					
	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
lm1 <-						
LM	1 (constrained)					
_cons	1.962264	.0319617	61.39	0.000	1.89962	2.024908
lm2 <-						
LM	.9604061	.0521401	18.42	0.000	.8582134	1.062599
_cons	1.985849	.0357795	55.50	0.000	1.915722	2.055976
lm3 <-						
LM	.7206433	.0358553	20.10	0.000	.6503681	.7909184
_cons	1.759434	.0247735	71.02	0.000	1.710879	1.807989
lm4 <-						
LM	.9031913	.0516355	17.49	0.000	.8019876	1.004395
_cons	2.193396	.036941	59.38	0.000	2.120993	2.265799

RQ6 – Were the students safe when communicating online?

A statistically significant and favorable effect was discovered in the path coefficient at the 0.001 level when examining the direct effect of the measurement variable (OCSE2) on the latent variable (OCSE). When examining the direct association between the measurement variable (OCSE 3) and the latent variable (OCSE), the path coefficient shows statistically significant and positive effects at the 0.001 level. Additionally, a statistically significant and favorable effect was discovered in the path coefficient at the 0.001 level when examining the direct effect on the relationship between the measurement variable (OCSE) and the latent variable (OCSE) (Table 8).

Table 8. The relationship between the measurement variable (OCSE) on the latent variable (OCSE)

Measurement	OIM					
	Coef.	Std. Err.	z	P > |z|	[95% Conf. Interval]	
ocse1 <-						
OCSE	1 (constrained)					
_cons	2.160377	.0395846	54.58	0.000	2.082793	2.237962
ocse2 <-						
OCSE	1.245413	.0626985	19.86	0.000	1.122526	1.3683
_cons	2.533019	.0426606	59.38	0.000	2.449406	2.616632
ocse3 <-						
OCSE	1.229836	.0652928	18.84	0.000	1.101865	1.357808
_cons	2.372642	.0423462	56.03	0.000	2.289645	2.455639
ocse4 <-						
OCSE	1.220243	.067478	18.08	0.000	1.087989	1.352498
_cons	2.485849	.0438687	56.67	0.000	2.399868	2.57183

5 DISCUSSION

This study serves as a useful contribution to the field of online education, particularly during a pandemic,. This baseline analysis of Kosovo's HEI students will present fresh research directions for the future. This study assessed students' readiness for online learning during the COVID-19 pandemic using the OLR measure created by Hung et al. [26]. Due to problems with convergent validity, the results showed that the OLR scale was not entirely applicable to HEI students in an emergency. Therefore, for all future research projects, it was necessary to develop a new scale or alter an existing one for evaluating HEI students in a pandemic-like scenario. For additional in-depth findings, this study might be repeated with students from different academic fields to examine their level of preparedness for online learning during COVID-19.

For administrators at universities, HEI leaders, and policymakers, some of the following practical implications exist: 1) Study participants claimed they lacked the confidence to ask questions during an online debate. The negative effects on their subpar academic achievement were significant. To increase their students' self-efficacy in online communication, HEI faculty must plan training and orientation programs for them. They might then make full use of the online learning opportunity and actively participate in it. 2) The course instructor should make a concerted attempt to involve every student in task-based online group discussions given that the students expressed a lack of control over their learning and time management concerns. This would promote student participation while prohibiting other disruptive behaviors like chatting, texting, playing online games, and other similar ones during an online class. 3) The university administration should build a robust monitoring mechanism to keep an eye on student behavior during online classes in order to play a significant role in this area.

6 CONCLUSION

The perceptions of the students' motivation for learning were poor. Policymakers may use this finding to develop and provide students with quick ICT courses.

These courses would aid in their ICT skill development and prepare them for the difficulties of online learning during the COVID-19 pandemic or any other upcoming emergency.

During the COVID-19 epidemic, students at HEIs made decisions about their online educational lives that were considerably more tailored to them and successful because they were inspired to learn in this e-learning environment. Students showed improved computer and internet readiness, online communication self-efficacy, and learning motivation.

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8 APPENDIX

Notes:
1. (/v# option or -set maxvar-) 5000 maximum variables

Checking for updates...
(Contacting http://www.stata.com)
host not found
http://www.stata.com did not respond or is not a valid update site
unable to check for updates; verify Internet settings are correct.

. use "C:\Users\Olugbenga Olusegun-O\Downloads\Robertasem.dta", clear

. sem (CSE -> cse1,) (CSE -> cse2,) (CSE -> cse3,) (CSE -> cse4,) (SDL -> sdl1,) (SDL ->
> sdl2,) (SDL -> sdl3,) (SDL -> sdl4,) (SDL -> sdl5,) (LC -> lc1,) (LC -> lc2,) (LC ->
> lc3,) (LC -> lc4,) (LM -> lm1,) (LM -> lm2,) (LM -> lm3,) (LM -> lm4,) (OCSE -> ocse
> 1,) (OCSE -> ocse2,) (OCSE -> ocse3,) (OCSE -> ocse4,), construct (_lexogenous, diagonal
>) latent (CSE SDL LC LM OCSE) cov (CSE*SDL CSE*LC CSE*LM SDL*LC SDL*LM SDL*OCSE LC*LM LC*OC
> SE LM*OCSE) nocapslatent

Endogenous variables

Measurement : cse1 cse2 cse3 cse4 sdl1 sdl2 sdl3 sdl4 sdl5 lc1 lc2 lc3 lc4 lm1 lm2 lm3 lm4 ocse1 ocse2 ocse3 ocse4

Exogenous variables

Latent: CSE SDL LC LM OCSE

Fitting target model:

Iteration 0: log likelihood = -44926.438
Iteration 1: log likelihood = -44737.044
Iteration 2: log likelihood = -44634.109 (not concave)
Iteration 3: log likelihood = -44592.147
Iteration 4: log likelihood = -44581.466
Iteration 5: log likelihood = -44580.369
Iteration 6: log likelihood = -44580.283
Iteration 7: log likelihood = -44580.283

```
Structural equation model                    Number of obs      =      1272
Estimation method = ml
Log likelihood     = -44580.283

 (1) [cse1] CSE = 1
 (2) [sdl1] SDL = 1
 (3) [lc1]LC = 1
 (4) [lm1] LM = 1
 (5) [ocse1] OCSE = 1
------------------------------------------------------------------------------
             |                OIM
             |      Coef.   Std. Err.      z    P>|z|  [95% Conf. Interval]
-------------+----------------------------------------------------------------
Measurement |
  cse1 <-    |
         CSE |          1 (constrained)
       _cons |   2.099057   .0368871    56.90   0.000     2.026759    2.171354
  -----------+----------------------------------------------------------------
  cse2 <-    |
         CSE |   1.015946   .0845375    12.02   0.000     .8502558    1.181637
       _cons |   2.429245   .0421873    57.58   0.000      2.34656    2.511931
  -----------+----------------------------------------------------------------
  cse3 <-    |
         CSE |   1.156538   .0876655    13.19   0.000     .9847169    1.328359
       _cons |   2.127358   .0349588    60.85   0.000      2.05884    2.195876
  -----------+----------------------------------------------------------------
  cse4 <-    |
         CSE |   1.456277   .1133134    12.85   0.000     1.234187    1.678368
       _cons |   2.514151   .0452829    55.52   0.000     2.425398    2.602904
  -----------+----------------------------------------------------------------
  sdl1 <-    |
         SDL |          1 (constrained)
       _cons |   3.188679   .0483242    65.99   0.000     3.093966    3.283393
  -----------+----------------------------------------------------------------
  sdl2 <-    |
         SDL |    .930782   .0763224    12.20   0.000     .7811929    1.080371
       _cons |   2.358491   .0447047    52.76   0.000     2.270871     2.44611
  -----------+----------------------------------------------------------------
  sdl3 <-    |
         SDL |   1.282123   .0900728    14.23   0.000     1.105584    1.458662
       _cons |   2.443396   .0422455    57.84   0.000     2.360597    2.526196
  -----------+----------------------------------------------------------------
  sdl4 <-    |
         SDL |   1.155227   .0855982    13.50   0.000     .9874572    1.322996
       _cons |   2.396226   .0420023    57.05   0.000     2.313903    2.478549
  -----------+----------------------------------------------------------------
  sdl5 <-    |
         SDL |   1.400348   .0971552    14.41   0.000     1.209927    1.590768
       _cons |   2.542453   .0441413    57.60   0.000     2.455938    2.628968
  -----------+----------------------------------------------------------------
```

```
lc1 <-      |
         LC |         1 (constrained)
      _cons |   2.471698   .0444751    55.57   0.000     2.384528    2.558868
------------+----------------------------------------------------------------
lc2 <-      |
         LC |   1.218371   .1066753    11.42   0.000     1.009292    1.427451
      _cons |   2.580189   .0441886    58.39   0.000     2.493581    2.666797
------------+----------------------------------------------------------------
lc3 <-      |
         LC |   1.262015   .1074989    11.74   0.000     1.051321    1.472709
      _cons |   2.150943   .0394517    54.52   0.000     2.073619    2.228267
------------+----------------------------------------------------------------
lc4 <-      |
         LC |   1.326088   .1214386    10.92   0.000     1.088072    1.564103
      _cons |   2.443396   .0425531    57.42   0.000     2.359994    2.526799
------------+----------------------------------------------------------------
lm1 <-      |
         LM |         1 (constrained)
      _cons |   1.962264   .0319617    61.39   0.000      1.89962    2.024908
------------+----------------------------------------------------------------
lm2 <-      |
         LM |   .9604061   .0521401    18.42   0.000     .8582134    1.062599
      _cons |   1.985849   .0357795    55.50   0.000     1.915722    2.055976
------------+----------------------------------------------------------------
lm3 <-      |
         LM |   .7206433   .0358553    20.10   0.000     .6503681    .7909184
      _cons |   1.759434   .0247735    71.02   0.000     1.710879    1.807989
------------+----------------------------------------------------------------
lm4 <-      |
         LM |   .9031913   .0516355    17.49   0.000     .8019876    1.004395
      _cons |   2.193396    .036941    59.38   0.000     2.120993    2.265799
------------+----------------------------------------------------------------
ocse1 <-    |
       OCSE |         1 (constrained)
      _cons |   2.160377   .0395846    54.58   0.000     2.082793    2.237962
------------+----------------------------------------------------------------
ocse2 <-    |
       OCSE |   1.245413   .0626985    19.86   0.000     1.122526      1.3683
      _cons |   2.533019   .0426606    59.38   0.000     2.449406    2.616632
------------+----------------------------------------------------------------
ocse3 <-    |
       OCSE |   1.229836   .0652928    18.84   0.000     1.101865    1.357808
      _cons |   2.372642   .0423462    56.03   0.000     2.289645    2.455639
------------+----------------------------------------------------------------
ocse4 <-    |
       OCSE |   1.220243    .067478    18.08   0.000     1.087989    1.352498
      _cons |   2.485849   .0438687    56.67   0.000     2.399868     2.57183
-------------+----------------------------------------------------------------
var (e. cse1) |    1.23524   .0602586                      1.122606    1.359175
var (e. cse2) |   1.752419   .0799669                      1.602491    1.916374
var (e. cse3) |   .8917449   .0526616                      .7942794     1.00117
var (e. cse4) |   1.557433   .0880494                      1.394076    1.739931
```

```
 var (e. sdl1) |    2.32117   .1002791                    2.132717    2.526274
 var (e. sdl2) |   1.979639   .0864385                    1.817269    2.156516
 var (e. sdl3) |   1.202868    .063392                    1.084824    1.333758
 var (e. sdl4) |   1.377618   .0663748                    1.253479    1.514051
 var (e. sdl5) |   1.205293   .0691276                    1.077143    1.348689
  var(e.lc1) |   2.041311   .0907887                    1.870903     2.22724
  var(e.lc2) |   1.779006   .0859327                    1.618308    1.955661
  var(e.lc3) |   1.223661   .0672291                    1.098741    1.362784
  var(e.lc4) |   1.468439   .0784443                    1.322466    1.630524
  var(e.lm1) |   .6005759   .0367883                    .5326323    .6771864
  var(e.lm2) |   .9837935   .0489345                    .8924104    1.084534
  var(e.lm3) |   .4177337   .0224414                    .3759857    .4641171
  var(e.lm4) |   1.165744   .0542374                    1.064144    1.277045
var (e. ocse1) |    1.20053   .0576413                    1.092708    1.318992
var (e. ocse2) |   1.085557   .0620031                    .9705881    1.214144
var (e. ocse3) |   1.082118   .0607002                    .9694549    1.207875
var (e. ocse4) |   1.267712   .0668898                    1.143161    1.405832
    var (CSE)|   .4955138   .0595218                     .391569    .6270516
    var (SDL)|   .6492383    .080871                    .5085996    .8287666
     var (LC)|   .4747532    .069789                    .3559104    .6332789
     var (LM)|   .6988341   .0521541                    .6037384    .8089085
   var (OCSE)|   .7926168   .0709683                    .6650426    .9446634
-------------+----------------------------------------------------------------
 cov (CSE, SDL) |    .199952   .0277697     7.20   0.000     .1455245    .2543796
  cov (CSE, LC) |   .1459831   .0243358     6.00   0.000     .0982859    .1936804
  cov (CSE, LM) |   .2687588   .0298804     8.99   0.000     .2101943    .3273233
  cov (SDL, LC) |   .3564166   .0406466     8.77   0.000     .2767508    .4360824
  cov (SDL, LM) |   .2112108   .0275964     7.65   0.000     .1571228    .2652988
cov (SDL, OCSE) |   .3056239   .0349426     8.75   0.000     .2371375    .3741102
   cov (LC, LM) |   .1583939   .0259718     6.10   0.000     .1074901    .2092977
 cov (LC, OCSE) |   .2130489   .0295816     7.20   0.000       .15507    .2710278
 cov (LM, OCSE) |   .2103696   .0284388     7.40   0.000     .1546307    .2661086
------------------------------------------------------------------------------
LR test of model vs. saturated: chi2(180) =   1883.15, Prob > chi2 = 0.0000
.
. eestategof, stats(all)

----------------------------------------------------------------------------
Fit statistic        |      Value   Description
---------------------+------------------------------------------------------
Likelihood ratio     |
       chi2_ms (180) |   1883.149   model vs. saturated
            p > chi2 |      0.000
       chi2_bs (210) |   7831.379   baseline vs. saturated
            p > chi2 |      0.000
---------------------+------------------------------------------------------
Population error     |
               RMSEA |      0.086   Root mean squared error of approximation
 90% CI, lower bound |      0.000
         upper bound |.
              pclose |      0.000   Probability RMSEA <= 0.05
---------------------+------------------------------------------------------
```

```
Information criteria |
                 AIC | 89304.566   Akaike's information criterion
                 BIC | 89675.247   Bayesian information criterion
---------------------+------------------------------------------------------
Baseline comparison |
                 CFI |      0.777   Comparative fit index
                 TLI |      0.739   TuckLewis'swis index
---------------------+------------------------------------------------------
Size of residuals    |
                SRMR |      0.067   Standardized root mean squared residual
                  CD |      0.997   Coefficient of determination
----------------------------------------------------------------------------

. predict CSE SDL LC LM OCSE, latent
(Latent (CSE SDL LC LM OCSE) assumed)

. predict CSE SDL LC LM OCSE, xblatent
option xblatent is not allowed for models without latent endogenous variables
r (198);

. predict CSE SDL LC LM OCSE, scores
CSE already defined
r (110);

. estat framework

Endogenous variables on endogenous variables

             | observed
        Beta |     cse1      cse2      cse3      cse4      sdl1      sdl2
-------------+------------------------------------------------------------
observed     |
        cse1 |        0
        cse2 |        0         0
        cse3 |        0         0         0
        cse4 |        0         0         0         0
        sdl1 |        0         0         0         0         0
        sdl2 |        0         0         0         0         0         0
        sdl3 |        0         0         0         0         0         0
        sdl4 |        0         0         0         0         0         0
        sdl5 |        0         0         0         0         0         0
         lc1 |        0         0         0         0         0         0
         lc2 |        0         0         0         0         0         0
         lc3 |        0         0         0         0         0         0
         lc4 |        0         0         0         0         0         0
         lm1 |        0         0         0         0         0         0
         lm2 |        0         0         0         0         0         0
         lm3 |        0         0         0         0         0         0
         lm4 |        0         0         0         0         0         0
```

```
       ocse1 |        0          0          0          0          0          0
       ocse2 |        0          0          0          0          0          0
       ocse3 |        0          0          0          0          0          0
       ocse4 |        0          0          0          0          0          0
-------------------------------------------------------------------------------

             | observed
        Beta |     sdl3       sdl4       sdl5        lc1        lc2        lc3
-------------+-----------------------------------------------------------------
observed     |
        sdl3 |        0
        sdl4 |        0          0
        sdl5 |        0          0          0
         lc1 |        0          0          0          0
         lc2 |        0          0          0          0          0
         lc3 |        0          0          0          0          0          0
         lc4 |        0          0          0          0          0          0
         lm1 |        0          0          0          0          0          0
         lm2 |        0          0          0          0          0          0
         lm3 |        0          0          0          0          0          0
         lm4 |        0          0          0          0          0          0
       ocse1 |        0          0          0          0          0          0
       ocse2 |        0          0          0          0          0          0
       ocse3 |        0          0          0          0          0          0
       ocse4 |        0          0          0          0          0          0
-------------------------------------------------------------------------------

             | observed
        Beta |      lc4        lm1        lm2        lm3        lm4      ocse1
-------------+-----------------------------------------------------------------
observed     |
         lc4 |        0
         lm1 |        0          0
         lm2 |        0          0          0
         lm3 |        0          0          0          0
         lm4 |        0          0          0          0          0
       ocse1 |        0          0          0          0          0          0
       ocse2 |        0          0          0          0          0          0
       ocse3 |        0          0          0          0          0          0
       ocse4 |        0          0          0          0          0          0
-------------------------------------------------------------------------------

             | observed
        Beta |    ocse2      ocse3      ocse4
-------------+---------------------------------
observed     |
       ocse2 |        0
       ocse3 |        0          0
       ocse4 |        0          0          0
-----------------------------------------------
```

Exogenous variables on endogenous variables

Gamma (observed)	latent CSE	SDL	LC	LM	OCSE
cse1	1	0	0	0	0
cse2	1.015946	0	0	0	0
cse3	1.156538	0	0	0	0
cse4	1.456277	0	0	0	0
sdl1	0	1	0	0	0
sdl2	0	.930782	0	0	0
sdl3	0	1.282123	0	0	0
sdl4	0	1.155227	0	0	0
sdl5	0	1.400348	0	0	0
lc1	0	0	1	0	0
lc2	0	0	1.218371	0	0
lc3	0	0	1.262015	0	0
lc4	0	0	1.326088	0	0
lm1	0	0	0	1	0
lm2	0	0	0	.9604061	0
lm3	0	0	0	.7206433	0
lm4	0	0	0	.9031913	0
ocse1	0	0	0	0	1
ocse2	0	0	0	0	1.245413
ocse3	0	0	0	0	1.229836
ocse4	0	0	0	0	1.220243

Covariances of error variables

Psi (observed)	observed e. cse1	e. cse2	e. cse3	e. cse4	e. sdl1	e. sdl2
e. cse1	1.23524					
e. cse2	0	1.752419				
e. cse3	0	0	.8917449			
e. cse4	0	0	0	1.557433		
e. sdl1	0	0	0	0	2.32117	
e. sdl2	0	0	0	0	0	1.979639
e. sdl3	0	0	0	0	0	0
e. sdl4	0	0	0	0	0	0
e. sdl5	0	0	0	0	0	0
e.lc1	0	0	0	0	0	0
e.lc2	0	0	0	0	0	0
e.lc3	0	0	0	0	0	0
e.lc4	0	0	0	0	0	0
e.lm1	0	0	0	0	0	0
e.lm2	0	0	0	0	0	0
e.lm3	0	0	0	0	0	0
e.lm4	0	0	0	0	0	0

```
   e. ocse1 |        0         0         0         0         0         0
   e. ocse2 |        0         0         0         0         0         0
   e. ocse3 |        0         0         0         0         0         0
   e. ocse4 |        0         0         0         0         0         0
------------------------------------------------------------------------------

          | observed
      Psi |   e. sdl3    e. sdl4    e. sdl5      e.lc1      e.lc2      e.lc3
-------------+------------------------------------------------------------------
observed     |
    e. sdl3 | 1.202868
    e. sdl4 |        0  1.377618
    e. sdl5 |        0         0  1.205293
      e.lc1 |        0         0         0  2.041311
      e.lc2 |        0         0         0         0  1.779006
      e.lc3 |        0         0         0         0         0  1.223661
      e.lc4 |        0         0         0         0         0         0
      e.lm1 |        0         0         0         0         0         0
      e.lm2 |        0         0         0         0         0         0
      e.lm3 |        0         0         0         0         0         0
      e.lm4 |        0         0         0         0         0         0
   e. ocse1 |        0         0         0         0         0         0
   e. ocse2 |        0         0         0         0         0         0
   e. ocse3 |        0         0         0         0         0         0
   e. ocse4 |        0         0         0         0         0         0
------------------------------------------------------------------------------

          | observed
      Psi |    e.lc4      e.lm1      e.lm2      e.lm3      e.lm4   e. ocse1
-------------+------------------------------------------------------------------
observed     |
      e.lc4 | 1.468439
      e.lm1 |        0  .6005759
      e.lm2 |        0         0  .9837935
      e.lm3 |        0         0         0  .4177337
      e.lm4 |        0         0         0         0  1.165744
   e. ocse1 |        0         0         0         0         0   1.20053
   e. ocse2 |        0         0         0         0         0         0
   e. ocse3 |        0         0         0         0         0         0
   e. ocse4 |        0         0         0         0         0         0
------------------------------------------------------------------------------

          | observed
      Psi |  e. ocse2   e. ocse3   e. ocse4
-------------+--------------------------------
observed     |
   e. ocse2 | 1.085557
   e. ocse3 |        0  1.082118
   e. ocse4 |        0         0  1.267712
---------------------------------------------
```

```
Intercepts of endogenous variables

             | observed
       alpha |     cse1      cse2      cse3      cse4      sdl1      sdl2
-------------+------------------------------------------------------------
       _cons | 2.099057  2.429245  2.127358  2.514151  3.188679  2.358491
--------------------------------------------------------------------------

             | observed
       alpha |     sdl3      sdl4      sdl5       lc1       lc2       lc3
-------------+------------------------------------------------------------
       _cons | 2.443396  2.396226  2.542453  2.471698  2.580189  2.150943
--------------------------------------------------------------------------

             | observed
       alpha |      lc4       lm1       lm2       lm3       lm4     ocse1
-------------+------------------------------------------------------------
       _cons | 2.443396  1.962264  1.985849  1.759434  2.193396  2.160377
--------------------------------------------------------------------------

             | observed
       alpha |    ocse2     ocse3     ocse4
-------------+------------------------------
       _cons | 2.533019  2.372642  2.485849
--------------------------------------------

Covariances of exogenous variables

             | latent
         Phi |      CSE       SDL        LC        LM      OCSE
-------------+--------------------------------------------------
latent       |
         CSE | .4955138
         SDL |  .199952  .6492383
          LC | .1459831  .3564166  .4747532
          LM | .2687588  .2112108  .1583939  .6988341
        OCSE |        0  .3056239  .2130489  .2103696  .7926168
----------------------------------------------------------------

Means of exogenous variables

             | latent
       kappa |      CSE       SDL        LC        LM      OCSE
-------------+--------------------------------------------------
        mean |        0         0         0         0         0
----------------------------------------------------------------
```

. factor cse1 cse2 cse3 cse4 sdl1 sdl2 sdl3 sdl4 sdl5 lc1 lc2 lc3 lc4 lm1 lm2 lm3 lm4 ocse1 o
> cse2 ocse3 ocse4
(obs=1272)

Factor analysis/correlation Number of obs = 1272
Method: principal factors Retained factors = 12
Rotation: (unrotated) Number of params = 186

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.44488	2.96982	0.5553	0.5553
Factor2	1.47507	0.28563	0.1843	0.7396
Factor3	1.18944	0.45622	0.1486	0.8882
Factor4	0.73322	0.09700	0.0916	0.9798
Factor5	0.63622	0.22956	0.0795	1.0593
Factor6	0.40666	0.11008	0.0508	1.1101
Factor7	0.29658	0.08340	0.0371	1.1471
Factor8	0.21318	0.05306	0.0266	1.1737
Factor9	0.16012	0.10469	0.0200	1.1937
Factor10	0.05543	0.03201	0.0069	1.2007
Factor11	0.02341	0.00812	0.0029	1.2036
Factor12	0.01530	0.03004	0.0019	1.2055
Factor13	-0.01474	0.07696	-0.0018	1.2037
Factor14	-0.09169	0.01876	-0.0115	1.1922
Factor15	-0.11046	0.05490	-0.0138	1.1784
Factor16	-0.16535	0.01383	-0.0207	1.1578
Factor17	-0.17919	0.03307	-0.0224	1.1354
Factor18	-0.21226	0.04113	-0.0265	1.1089
Factor19	-0.25339	0.02823	-0.0317	1.0772
Factor20	-0.28162	0.05467	-0.0352	1.0420
Factor21	-0.33629	.	-0.0420	1.0000

LR test: independent vs. saturated: chi2(210) = 7783.15 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Factor7
cse1	0.3409	0.3047	0.2036	0.2511	-0.0699	-0.0431	-0.1211
cse2	0.3575	0.0480	0.1478	0.3599	-0.1484	-0.1241	-0.0502
cse3	0.4051	0.2946	0.1340	0.3384	0.0209	-0.0509	0.0897
cse4	0.4473	0.1093	0.2414	0.3331	0.0064	0.1310	0.1150
sdl1	0.4402	-0.2956	0.0961	0.1419	0.0592	0.2054	-0.1035
sdl2	0.4728	-0.1147	0.1479	-0.0745	0.0687	-0.0545	-0.2528
sdl3	0.5313	-0.2484	0.2106	-0.1591	-0.2665	-0.0325	-0.0850
sdl4	0.5405	-0.1500	0.0388	-0.1883	-0.2939	0.0298	-0.0871
sdl5	0.5855	-0.2203	0.2037	-0.1113	-0.3414	0.1516	0.1845
lc1	0.3478	-0.1671	0.1824	-0.0375	0.3192	0.2811	0.0686
lc2	0.3671	-0.2483	0.1665	-0.1533	0.1739	-0.1137	0.2391
lc3	0.4221	-0.2031	0.1815	-0.1039	0.2932	-0.1485	0.0022
lc4	0.4703	-0.1423	0.2081	-0.0508	0.1581	-0.3012	-0.0295
lm1	0.4876	0.4827	-0.0015	-0.1482	0.1279	0.0921	0.0847
lm2	0.4802	0.3819	-0.0352	-0.0368	0.0868	0.0365	-0.0223
lm3	0.4331	0.5059	0.0366	-0.2910	0.1024	0.0363	-0.1395
lm4	0.3687	0.4276	-0.1456	-0.2147	-0.2022	-0.0598	0.1235

ocse1	0.4267	-0.1054	-0.4585	0.0403	0.0488	0.2104	-0.0781
ocse2	0.5501	-0.1317	-0.4147	0.0953	0.0633	-0.0000	-0.0934
ocse3	0.5389	-0.0404	-0.4833	0.0875	-0.0253	-0.1794	0.0932
ocse4	0.5294	-0.2216	-0.3932	0.0743	0.0351	-0.0608	0.0771

Variable	Factor8	Factor9	Factor10	Factor11	Factor12	Uniqueness
cse1	-0.0003	0.1630	0.0822	0.0000	0.0488	0.6294
cse2	0.0924	0.0670	-0.0806	0.0076	0.0160	0.6588
cse3	-0.1120	-0.0248	0.0352	0.0065	-0.0507	0.5886
cse4	-0.1037	-0.1033	-0.0042	0.0124	-0.0251	0.5661
sdl1	0.1640	-0.1017	0.0406	0.0142	0.0184	0.5937
sdl2	0.0663	-0.1392	-0.0239	0.0602	-0.0121	0.6362
sdl3	0.0782	0.1321	0.0111	0.0032	-0.0560	0.4801
sdl4	-0.2457	-0.0603	0.0020	0.0055	0.0241	0.4890
sdl5	0.0407	-0.0056	-0.0166	-0.0471	0.0151	0.3768
lc1	-0.0130	0.1055	0.0244	0.0145	0.0354	0.6174
lc2	0.0502	0.0888	-0.0205	0.0659	-0.0177	0.6365
lc3	-0.0286	0.0321	0.0391	-0.0681	-0.0144	0.6206
lc4	-0.1183	-0.0633	-0.0436	-0.0270	0.0333	0.5744
lm1	-0.0240	-0.0406	-0.0948	0.0183	0.0209	0.4632
lm2	0.1765	-0.0436	-0.0382	-0.0734	-0.0160	0.5714
lm3	-0.0339	0.0420	0.0684	0.0113	-0.0184	0.4311
lm4	0.0863	-0.0359	0.0300	0.0254	0.0152	0.5437
ocse1	-0.1435	0.0840	-0.0293	-0.0109	-0.0253	0.5129
ocse2	0.0242	0.0773	-0.0817	-0.0016	-0.0007	0.4730
ocse3	0.0110	0.0590	0.0337	0.0217	0.0153	0.4198
ocse4	0.0534	-0.1406	0.0958	-0.0087	0.0041	0.4677

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