TYPE Original Research
PUBLISHED 03 November 2022
DOI 10.3389/feduc.2022.916721

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SPECIALTY SECTION
This article was submitted to Digital Education, a section of the journal Frontiers in Education

RECEIVED 09 May 2022
ACCEPTED 22 September 2022
PUBLISHED 03 November 2022

CITATION
Prabowo H, Ikhsan RB and Yuniarty Y (2022) Student performance in online learning higher education: A preliminary research. *Front. Educ.* 7:916721. doi: 10.3389/feduc.2022.916721

Student performance in online learning higher education: A preliminary research

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The impact of student performance is the focus of online learning because it can determine the success of students and higher education institutions to get good ratings and public trust. This study explores comprehensively the factors that can affect the impact of student performance in online learning. An empirical model of the impact of student performance has been developed from the literature review and previous research. The test of reliability and validity of the empirical model was evaluated through linguist reviews and statistically tested with construct reliability coefficients and confirmatory factor analysis (CFA). Overall, the results of this study prove that the structural model with second-order measurements produces a good fit, while the structural model with first-order measurements shows a poor fit.

KEYWORDS

overall quality, course quality, e-learning technology, online learning, student engagement, student and institutional factors, instructor characteristics, student performance

Introduction

Apart from the COVID-19 disaster, since 2021, the Indonesian government has launched a distance education system as the forerunner of e-learning. This system brings new colors to the learning process and challenges to adopt and innovate learning. The success of a learning system is highly dependent on mixed conditions, including the learning environment, teaching methods, resources, and learning expectations.

Many developed countries have integrated e-learning systems in higher education, but Indonesia, as a developing country, has not effectively adopted this technology. Several previous studies have acknowledged the severe challenges that hinder the integration of quality e-learning in universities, particularly in developing countries (Al-Adwan et al., 2021; Basir et al., 2021). Therefore, the various benefits of e-learning as a mode of education to improve the teaching-learning process and the barriers and challenges to adopting e-learning technology must also be considered.

The characteristics of students who take online education are different from students who apply traditional learning systems. Broad reach, a high level of flexibility, and easy access are reasons for students who are just starting a career in companies and professionals to improve their careers. For this reason, universities are campaigning for the efficiency of online education to meet the needs of students (Paul and Pradhan, 2019) resulting in a big boom in the education technology (EdTech) segment (Semeshkina, 2021).

The use of technology in online learning can improve the quality of learning, help students' complete assignments quickly, gain insight and skills. In this study, the meaning of the impact of online learning performance is that online learning abilities can affect student performance in saving resources, productivity, competence, and knowledge (Aldholay et al., 2018). Universities need to pay attention to factors that can improve online learning performance by increasing student satisfaction and involvement.

The researchers succeeded in investigating the determinants of student performance in the context of online learning (Zimmerman and Nimon, 2017; Aldholay et al., 2018; Büchele, 2021). The scope of their study is limited to student factors in learning and college infrastructure as education service providers. This study extends the results of previous researchers by examining input factors [course quality (Jaggars and Xu, 2016; Debattista, 2018), instructor (Daouk et al., 2016), student, institutional (Hadullo et al., 2018), and technology (Kissi et al., 2018; Almaiah and Alismaiel, 2019; Sheppard and Vibert, 2019; Ameri et al., 2020; Yadegaridehkordi et al., 2020)], output [overall quality (Aldholay et al., 2018; Hadullo et al., 2018; Almaiah and Alismaiel, 2019; Thongsri et al., 2019)] and outcome [engagement (Büchele, 2021), satisfaction and performance (Aldholay et al., 2018)] during the online learning process. Based on the experience and knowledge of researchers, these factors can improve the performance of online learning students. This study aims to propose a conceptual framework for students' performance impact in online learning (**Figure 1**). Therefore, specifically this paper as a preliminary study in the development of a predetermined model.

Literature review

Online learning in higher education

Online learning has become an appropriate and attractive solution for students who pursue their education while undergoing busy activities (Seaman et al., 2018). Therefore, universities are constantly looking for ways to improve the quality of online courses to increase student satisfaction, enrollment, and retention (Legon and Garrett, 2017).

A unique feature of online learning is that students and lecturers are physically far apart and require a medium for delivering course material (Wilde and Hsu, 2019). The interaction of students and lecturers is mediated by technology, and the design of virtual learning environments significantly impacts learning outcomes (Bower, 2019; Gonzalez et al., 2020). For decades, research on online learning has been studied, and the effectiveness of online teaching results from instructional design and planning (Hodges et al., 2020). The COVID-19 pandemic is forcing students worldwide to shift from offline learning to online learning environments. Students and teachers have limited capacities regarding information processing, and there is a chance that a combination of learning modalities may result in the cognitive overload that impacts the ability to learn new information effectively (Patricia Aguilera-Hermida, 2020). In addition, lack of confidence in the new technology they use for learning or the absence of cognitive engagement and social connections have less than the optimal impact on student learning outcomes (Bower, 2019).

The existence of technology, if used effectively, can provide opportunities for students and teachers to collaborate (Bower, 2019; Gonzalez et al., 2020). The success of the transition from offline to online learning is strongly influenced by the intention and usefulness of technology (Yakubu and Dasuki, 2018; Kemp et al., 2019), so the effectiveness of online learning is highly dependent on the level of student acceptance (Tarhini et al., 2015). Therefore, it is essential to analyze the factors related to online learning to achieve student learning outcomes.

Course quality

As online learning continues to mature and evolve in higher education, faculty and support staff (instructional designers, developers, and technologists) need guidance on how to best design and deliver practical online courses. Course quality standards are a valuable component in the instructional design process. They help guide course writers and identify needed improvements in courses and programs and create consistency in faculty expectations and student experience (Scharf, 2017).

In general, quality is an essential factor in online learning to provide a helpful learning experience for students (Barczyk et al., 2017), while course quality supports university learning performance. Quality Matters^{TM} (QM) is an international organization that involves collaboration between institutions and creating a shared understanding of online course quality (Ralston-Berg, 2014). This research measures course quality by three dimensions: course design, course content support, and course assessment (Hadullo et al., 2018). These three dimensions are determinants in assessing the quality of learning.

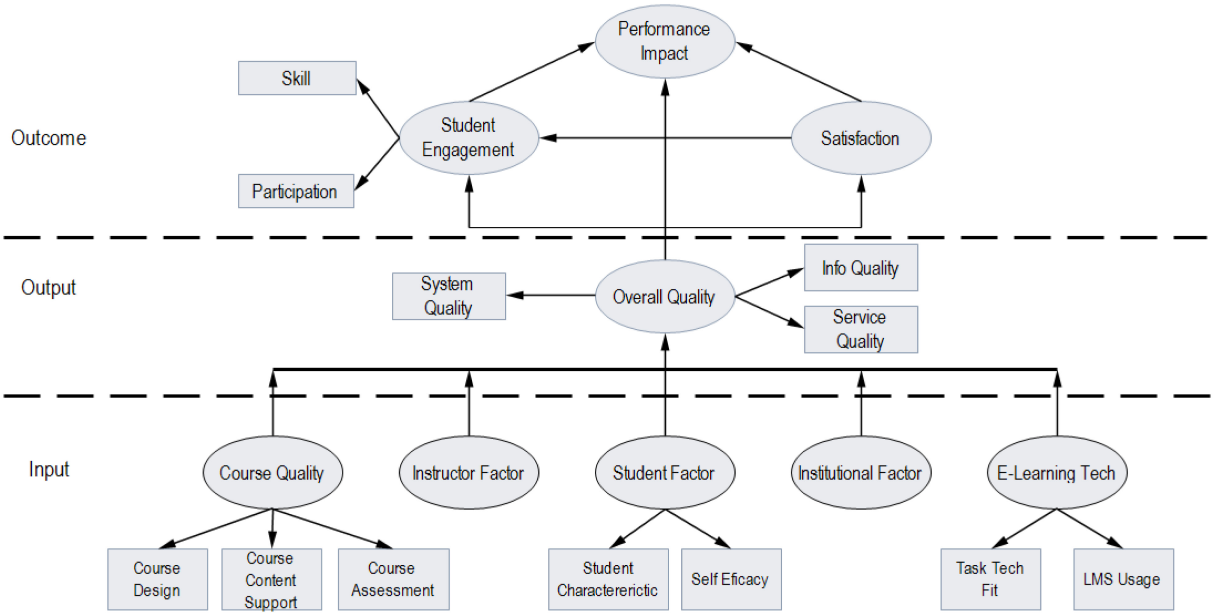

FIGURE 1
Framework of student performance in online learning setting.

Instructor factor

The quality of the instructor in delivering the material becomes the input to achieve learning performance (Ikhsan et al., 2019). To facilitate an active learning process, instructors should use strategies to increase participation in learning. While the responsibility for learning lies with the learner, the instructor plays an essential role in enhancing learning and engagement in the online environment (Arghode et al., 2018). As an essential actor in the classroom, instructors must have psychological similarities with students to help academically lacking students by changing perceptions of external barriers and stereotypes (Sullivan et al., 2021).

Several research results have proven the influence of instructor interactivity in the classroom on online teaching, including active learning (Muir et al., 2019), instructor presence (Roque-Hernández et al., 2021), discussion and assessment techniques (Chakraborty et al., 2021; McAvoy et al., 2022), and feedback (Kim and Kim, 2021). Some of these study areas are topics often studied with the needs and values of instructor interaction. In this study, the importance of instructor interactivity in online learning is related to online discussion forum activities and instructor interaction.

Student factor

The characteristics of students who take online learning education are different from those who study conventionally (face to face). Several essential factors drive student success in online learning: understanding computers and the internet, personal desires, motivation from instructors, and reasonable access to online learning systems (Hadullo et al., 2018; Bashir et al., 2021; Glassman et al., 2021; Rahman et al., 2021). Self-efficacy is explained by social cognitive theory as the ability to self-regulation (Bandura, 2010). According to social cognitive theory, people can develop self-efficacy by observing other people's models of achieving goals and having had various successful attempts in the past to achieve challenging goals (Duchatelet and Donche, 2019). People who have high levels of self-efficacy tend to be confident in their ability to succeed in challenging tasks, such as their own, and observe others to achieve goals.

Institutional factor

Institutional theory has been used to explore organizational behavior toward technology acceptance, as it explains how institutions adapt to institutional change (Rohde and Hielscher, 2021). Currently, most higher education institutions have migrated from traditional to online learning systems, thereby changing traditional learning environments such as the physical presence of teachers, classrooms, and exams (Bokolo et al., 2020). Today's developing technologies have improved education due to online learning, teleconferencing, computer-assisted learning, web-based distance learning, and other technologies (Bailey et al., 2022; Fauzi, 2022). Online learning systems provide more flexibility and improve teaching and learning processes, offering more opportunities for reflection and feedback (Archambault et al., 2022). Online learning offers interactive teaching, easy access, and is cost-effective mainly (Sweta, 2021).

E-learning technology

E-learning technology in this study is defined as the learning media used by universities in going online learning. The task-technology fit (TTF) model has been used to assess how technology generates performance, evaluate the effect of use and assess the fit between task requirements and technological competence (Wu and Chen, 2017). The TTF model suggests that the user accepts the technology because it is appropriate to the task and improves learning performance (Kissi et al., 2018). Technology acceptance is determined by the individual's understanding and attitude toward technology, but the compatibility between task and technology must be considered necessary (Zhou et al., 2010). When a student decides to use technology, such as an LMS, their decision is very likely that the assignment and technology match.

Overall quality

Developments and challenges in information systems inspire researchers and practitioners to improve the quality and functionality of a new system to take advantage of its growth potential (Aldholay et al., 2018). Overall quality is understood as a new construct that includes system quality, information quality, and service quality (Ho et al., 2010; Isaac et al., 2017d). *System quality* is defined as the extent to which users believe that the system is easy to use, easy to learn, easy to connect, and fun to use (Jiménez-Bucarey et al., 2021). Information quality is understood as the extent to which system users think that online learning information is up-to-date, accurate, relevant, comprehensive, and organized (Raija et al., 2010). Service quality is referred to through various attributes, such as tangible, reliability, responsiveness, assurance, functionality, interactivity, and empathy (Preaux et al., 2022).

Student engagement

Student engagement in online learning is when they use online learning platforms to learn, including behavioral, cognitive, and emotional engagement (Hu et al., 2016). Student engagement in online learning is not only due to the behavioral performance of reading teaching materials, asking questions, participating in interactive activities, and completing homework, but more importantly, cognitive performance (Lee et al., 2015). In this study, cognitive behavior is all mental activities that enable students to relate, assess, and consider an event to gain knowledge afterward. In addition, cognitive behavior is closely related to a person's intelligence and skill level. For example: when someone is studying, building an idea, and solving a problem.

Student behavioral engagement is essential in online learning but is difficult to define clearly and fully reflect student efforts. So, it must consider students' perception, regulation, and emotional support in the learning process (ChanMin et al., 2015). Students must fully enter online learning, including the quantity of engagement and quality of engagement, communication with others and conscious learning, guidance, assistance from others, and self-management and self-control.

Student satisfaction

Perceived satisfaction is not limited to marketing concepts but can also be used in the context of online learning (Caruana et al., 2016). User satisfaction is one of the leading indicators when assessing success in adopting a new system (Montesdioca and Maçada, 2015; DeLone and McLean, 2016). User satisfaction also refers to perceiving a system as applicable and wanting to reuse it. In the context of online learning, student satisfaction is defined as the extent to which students who use online learning are satisfied with their decision to use it and how well it meets their expectations (Roca et al., 2006). Students who are satisfied while studying with an online learning system will strive to achieve good academic scores.

Student performance impact

In the context of education, performance is the result of the efforts of students and lecturers in the learning process and students' interest in learning (Mensink and King, 2020). The essence of education is student academic achievement; therefore, student achievement is considered the success of the entire education system. Student academic achievement determines the success and failure of academic institutions (Narad and Abdullah, 2016).

It is crucial to explore problems with online learning systems in higher education to improve the student experience in learning. Therefore, the university's ability to design effective online learning will impact university performance and student performance. The failure of online learning design and technology can frustrate students and lead to negative perceptions of students (Gopal et al., 2021).

With rapidly changing technology and the introduction of many new systems, researchers focus on the results of using systems in terms of performance improvement to evaluate and measure system success (Montesdioca and Maçada, 2015; Isaac et al., 2017a,b,c,d). *Performance impact* is defined as the extent to which the use of the system improves the quality of work by helping to complete tasks quickly, enabling control over work, improving job performance, eliminating errors, and increasing work effectiveness (Isaac et al., 2017d; Aldholay et al., 2018). In this study, performance impact is interpreted as an outcome of the use of technology in online learning.

Materials and methods

Participants

As a preliminary study, this study involved 206 students at a private university in Jakarta, Indonesia. At the university, only five study programs fully implement the online learning system. Therefore, we decided to take all study programs as the unit of analysis. This study involved 206 students at a private university in Jakarta, Indonesia, who implemented an online learning system. Those who participated came from five study programs: Management Department, Accounting Department, Information System Department, Computer Science Department, and Industrial Engineering. Sampling used stratified sampling, and each study program received about 41–42 responses. Researchers sent questionnaires to each head of the department to distribute to students online. All questionnaires were successfully received within 1 week. Each participant received a souvenir for taking 15–20 min to answer all the questions in the questionnaire.

A total of 206 data were collected, 96 female students and 110 male students. 108 students access the LMS between 1–3 h a day, 75 students access the LMS less than 3 h per day, and 23 students access the LMS more than 3 h per day. The average employment status of students is private employees (n = 127), as entrepreneurs (n = 10) and the rest are only as students (n = 69) (**Table 1**).

Questionnaire development

The questionnaire used in this study results from several prior studies following the research context, i.e., online learning. In detail can be seen in **Table 2**. The first draft of the questionnaire containing 80 statement items was tested virtually on ten students and one Indonesian language expert to ensure that each statement was easy to understand. Furthermore, all items must be answered using a 5-point Likert scale, from (1) strongly disagree to (5) strongly agree.

TABLE 1 Demographic of participants (n = 206).

Demographic	Frequency	Percent
Gender		
Male	96	46.6%
Female	110	53.4%
Students access the LMS		
Less than 1 h per day	75	36.4%
1–3 h per day	108	52.4%
More than 3 h per day	23	11.2%
Job		
Private employee	127	61.7%
Entrepreneur	10	4.9%
Student	69	33.5%

Validation process

The first step in the questionnaire item validation procedure starts from the pre-test and linguist review. Then the empirical data collected was calculated using Confirmatory Factor Analysis (CFA) and Construct Reliability (CR) analysis as a condition for construct validity and internal consistency.

CFA is a statistical tool helpful in finding the form of the construct of a set of manifest variables or testing a variable on the manifest assumptions that build it. Therefore, confirmatory analysis is suitable for testing a theory of variables on the manifest or the indicators that build it. The variables are assumed only to be measured by these indicators (Hair et al., 2019). The CFA results show that the multiple items in the questionnaire measure construct as hypothesized by the underlying theoretical framework. The CFA produces empirical evidence of the validity of scores for the instrument based on the established theoretical framework (George and Mallery, 2019). Construct reliability (CR) measures the internal consistency of the indicators of a variable that shows the degree to which the variables are formed. The limit value of the construct reliability test is accepted if the value is > 0.70 (Hair et al., 2019).

In the Structural Equation Modeling (SEM) framework, both variance and covariance-based, a questionnaire is valid if the loading factor value is 0.5 for analysis of covariance (Hair et al., 2019) and 0.7 for analysis of variance (Hair Joseph et al., 2019). In addition, the average variance extracted (AVE) value is more than 0.5 (Hair et al., 2019). In CFA, several goodness indices such as Chi-square (X^2), Normed Chi-Square (NCS) (X^2/df), Root Mean Square Error of Approximation (RSMEA), and Comparative Fit Index (CFI) were calculated to assess the model fit of the model framework under research (Kline, 2015).

Chi-square, NCS, and RMSEA statistics as absolute fit indices can be used to indicate the quality of the theoretical model being tested (Kline, 2015; Hair et al., 2019). The

TABLE 2 Measurement of construct.

Construct	Dimension	Code	Item	Source
Course quality	Course design	CD1	Our course id provided by information about the duration, list of books, availability of instructor	Hadullo et al., 2018
		CD2	Our course has an attractive and consistent layout improves quality	
		CD3	Our course has relevant, accurate, complete content aligned to objectives	
		CD4	Our course has a well sequenced content neatly arranged in headings and subheadings	
	Course content support	CCS1	The online learning system uses attractive multimedia features	
		CCS2	Online learning system using discussion and chat forums	
		CCS3	Online learning system using video and animation	
	Course assessment	CA1	The online learning system applies online quizzes and personal assessment tests	
		CA2	The online learning system uses a clear course assessment method	
		CA3	The online learning system promises timely feedback from lecturers	
Student factor	Student characteristics	SC1	I have computer and internet experience	Hadullo et al., 2018
		SC2	I am self-motivated to use e-learning	
		SC3	Our instructors motivate us in e-learning	
		SC4	We have learner-to-learner interactions in out courses	
	Self-efficacy	SE1	I feel confident finding information by using a search engine	Aldholay et al., 2018
		SE2	I feel confident in the online learning sending and receiving e-mail messages	
		SE3	I feel confident in the online learning downloading and uploading files	
E-learning tech	Task-technology fit	TTF1	I think that using LMS would be well suited for the way I like to learn tasks	Kissi et al., 2018
		TTF2	LMS would a good standard to support the way to learn	
		TTF3	I think that using LMS would be a good way to learn tasks.	
	LMS usage	LMS1	Regularly use LMS	Almaiah and Alismaiel, 2019; Ameri et al., 2020
		LMS2	Pleasant experience when using LMS	
		LMS3	I use LMS currently	
		LMS4	I spend a lot of time to use LMS	
Overall quality	System quality	SYQ1	I find the online learning to be easy to use	Aldholay et al., 2018
		SYQ2	I find the online learning to be flexible to interact with	
		SYQ3	My interaction with the online learning is clear and understandable	
	Information quality	IQ1	Online learning provides up-to-date knowledge	
		IQ2	Online learning provides accurate knowledge	
		IQ3	Online learning provides relevant knowledge	
		IQ4	Online learning provides comprehensive knowledge	
		IQ5	Online learning provides organized knowledge	
	Service quality	SQ1	I could use the online learning services at anytime, anywhere I want	
		SQ2	Online learning offers multimedia (audio, video, and text) types of course content	
		SQ3	Online learning enables interactive communication	
		SQ4	Get convenience when registering and there is a call center available	
Student engagement	Skill	SK1	I put forth effort in the tutorials.	Büchele, 2021

(*Continued*)

TABLE 2 (Continued)

Construct	Dimension	Code	Item	Source
		SK2	I take good notes in the tutorials.	
		SK3	I am looking over the tutorial notes on a regular basis, to make sure I understand the material.	
		SK4	I am listening carefully in the tutorials.	
		SK5	I make sure to prepare the tutorials on a regular basis.	
		SK6	I am well organized in the tutorials.	
		SK7	I do all the exercises.	
	Participation	PAR1	I raise my hands often in the video conference.	
		PAR2	I participate actively in small-group discussions.	
		PAR3	I help my fellow students, if necessary.	
		PAR4	I have fun in the video conference.	
		PAR5	I ask questions if I don't understand something.	
Institutional factors		IF1	Colleges have internet infrastructure with high internet speed	Hadullo et al., 2018
		IF2	Colleges have good online learning policies	
		IF3	Colleges have an institutional culture that supports online learning	
		IF4	Colleges are serious about building a good online learning system	
Instructor characteristics		IC1	Our instructors are very enthusiastic in teaching	Daouk et al., 2016
		IC2	Instructors use non-lecture learning activities such as small group discussions, student-led activities.	
		IC3	Our instructor invites class discussion	
		IC4	Our instructors combine simulations and real-world cases	
		IC5	Our instructors use teaching tools and materials, such as videos	
		IC6	Our instructors are aware of the learning needs of individual students	
		IC7	Our instructor explains the concept clearly	
		IC8	Our instructors connect concepts to student experiences	
		IC9	Our instructors prefer active, collaborative, and cooperative learning over passive learning	
		IC10	Our instructors actively encourage students to ask questions	
		IC11	Instructors often ask questions to monitor student understanding	
		IC12	When necessary, our instructors ask probing questions	
		IC13	Our instructors keep students' attention	
		IC14	Our instructors assess students through observing their oral performance such as discussions, presentations, and group work	
		IC15	Our instructors use humor appropriately to reinforce retention and interest	
Satisfaction		SAT1	My decision to use the online learning was a wise one	Aldholay et al., 2018
		SAT2	The online learning has met my expectations	
		SAT3	Overall, I am satisfied with the online learning	
Performance impact		PI1	Online learning helps me to accomplish my tasks more quickly	Aldholay et al., 2018
		PI2	Online learning makes it easier to complete my tasks	
		PI3	Online learning saves my money	
		PI4	Online learning improves my learning performance	
		PI5	Online learning enhances my academic effectiveness	
		PI6	Online learning helps reviews and eliminate errors in my work tasks	
		PI7	Online learning helps me to realize my future target	
		PI8	Online learning helps me acquire new knowledge	
		PI9	Online learning helps me acquire new skills	
		PI10	Online learning helps me to come up with innovative ideas	

TABLE 3 Confirmatory factor analysis and internal consistency—second order.

Variable	Dimension	SLF 2nd	Item	Mean	SLF 1st	AVE	CR
Overall quality	System quality	0.899	SYQ1	4.282	0.771	0.608	0.822
			SYQ2	4.180	0.704		
			SYQ3	3.893	0.857		
	Information quality	0.994	IQ1	4.063	0.750	0.672	0.911
			IQ2	4.024	0.825		
			IQ3	4.121	0.869		
			IQ4	4.029	0.832		
			IQ5	4.078	0.818		
	Service quality	0.693	SQ1	4.417	0.587	0.652	0.875
			SQ2	4.345	0.555		
			SQ3	3.927	0.986		
			SQ4	3.908	0.991		
Student engagement	Skill	0.936	SK1	4.286	0.634	0.551	0.895
			SK2	3.806	0.767		
			SK3	3.927	0.796		
			SK4.	4.150	0.727		
			SK5	4.063	0.795		
			SK6	4.029	0.810		
			SK7	4.432	0.647		
	Participation	0.889	PAR1	3.694	0.751	0.614	0.888
			PAR2	4.233	0.841		
			PAR3	4.117	0.781		
			PAR4	3.767	0.770		
			PAR5	4.228	0.771		
Course quality	Course design	0.966	CD1	3.995	0.711	0.598	0.855
			CD2	4.083	0.847		
			CD3	4.034	0.796		
			CD4	4.306	0.731		
	Course content support	0.882	CCS1	4.282	0.813	0.658	0.852
			CCS2	4.383	0.854		
			CCS3	4.282	0.764		
	Course assessment	0.904	CA1	4.257	0.839	0.626	0.833
			CA2	4.160	0.809		
			CA3	3.966	0.720		
Student factor	Student characteristics	0.716	SC1	4.209	0.863	0.623	0.868
			SC2	4.097	0.801		
			SC3	3.981	0.704		
			SC4	4.063	0.781		
	Self-efficacy	0.843	SE1	4.160	0.761	0.536	0.775
			SE2	4.388	0.799		
			SE3	4.097	0.626		
E-learning tech	Task-technology fit	0.868	TTF1	4.044	0.923	0.807	0.926
			TTF2	4.078	0.914		
			TTF3	4.019	0.857		
	LMS usage	0.924	AU1	3.966	0.803	0.622	0.868
			AU2	4.024	0.841		
			AU3	4.218	0.777		
			AU4	3.743	0.730		

TABLE 4 Confirmatory factor analysis and internal consistency—first order.

Construct	Item	Mean	SLF 1st	AVE	CR
Institutional factors	IF1	4.199	0.768	0.589	0.851
	IF2	4.228	0.767		
	IF3	4.286	0.734		
	IF4	4.112	0.799		
Instructor characteristics	IC1	3.932	0.734	0.561	0.950
	IC2	4.058	0.724		
	IC3	4.248	0.757		
	IC4	4.233	0.775		
	IC5	4.092	0.783		
	IC6	4.112	0.830		
	IC7	4.155	0.799		
	IC8	4.233	0.842		
	IC9	4.209	0.728		
	IC10	4.087	0.737		
	IC11	3.951	0.636		
	IC12	3.966	0.741		
	IC13	4.058	0.777		
	IC14	3.961	0.728		
	IC15	4.068	0.609		
Satisfaction	SAT1	4.223	0.831	0.765	0.907
	SAT2	4.073	0.900		
	SAT3	4.184	0.891		
Performance impact	PI1	3.995	0.775	0.642	0.946
	PI2	4.078	0.772		
	PI3	4.141	0.547		
	PI4	4.005	0.863		
	PI5	4.053	0.874		
	PI6	3.951	0.818		
	PI7	4.180	0.881		
	PI8	4.291	0.840		
	PI9	4.214	0.788		
	PI10	4.117	0.800		

X^2-test shows the difference between the observed and expected covariance matrices. Therefore, the smaller the X^2-value indicates a better fit model (Gatignon, 2010). The X^2-test should be insignificant for models with an acceptable fit. However, the statistical significance of the X^2-test results is very sensitive to the sample size (Kline, 2015; Hair et al., 2019). Therefore, the NCS should also be considered. NCS is equal to Chi-square divided by degrees of freedom (X^2/df). A smaller NCS value indicates a better model fit, and a NCS value equal to or less than 5 supports a good model fit (West et al., 2012; Hair et al., 2019). Another fit index model is the RMSEA. The RMSEA qualifies for the difference between the population covariance matrix and the theoretical model. An RMSEA value smaller than 0.08 indicates a better model and limits acceptable model fit (Gatignon, 2010; West et al., 2012; Hair et al., 2019). CFI was used to assess model fit in this study. If the CFI value is greater than 0.90, an acceptable model fit is indicated (Kline, 2015; Hair et al., 2019). The alpha (α) level in this study was set at 0.05 for the goodness-of-fit chi-square test (X^2).

Results

Descriptive analyses

Based on descriptive analysis (**Tables 3**, **4**), the mean value of overall quality items is in the interval range of 3.893 (SYQ3) to 4.417 (SQ1). It shows that students have given positive responses to all overall quality items. Furthermore, the mean value of student engagement items is in the interval range of 3.694 (PAR1) to 4.432 (SK7), which means that students give positive responses to all student engagement items. In the course quality construct, the mean value ranges from 3.966 (CA3) to 4.306 (CD4). That is, all students gave positive responses to the course quality items. The mean value of the student factor is in the range of 3.981 (SC3) to 4.388 (SE2). In e-learning technology, the mean value ranges from 3.743 (AU4) to 4,218. Students gave a positive response to the student factor and e-learning technology. Finally, on the constructs of institutional factors, instructor characteristics, satisfaction, and performance impact, the average student responded positively to all statement items because the mean value was in the range of 3.932–4.291. It can be concluded that all students gave a positive response to all the constructs measured in this study.

Normality test

Hair et al. (2019) illustrated that testing absolute data normality in multivariate analysis. If the data is not normally distributed, it can affect the validity and reliability of the results. In this study, we used the One-Sample Kolmogorov-Smirnov Test with the Monte Carlo method (Metropolis and Ulam, 1949). As a result, the significance value of Monte Carlo is $0.120 > 0.05$. The data used in testing the validity and reliability is normally distributed.

The result of internal consistency and confirmatory factor analysis

Tables 3, **4** presents the overall results of the validity and reliability tests which are CFA, AVE, and CR analyzed. The construct concept can be unidimensional or multidimensional, which impacts testing its validity and reliability. The construct is in unidimensional validity and reliability testing using CFA first order. It is multidimensional and

TABLE 5 Discriminant validity (Fornell-Lacker).

SyQ	IQ	SQ	SK	Par	CD	CCS	CA	SCI	SE	TTF	AU	IF	IC	SAT	PI	
SyQ	**0.780**															
IQ	0.733	**0.820**														
SQ	0.639	0.663	**0.807**													
SK	0.591	0.673	0.636	**0.742**												
Par	0.558	0.616	0.602	0.740	**0.784**											
CD	0.718	0.807	0.685	0.690	0.629	**0.773**										
CCS	0.593	0.692	0.653	0.633	0.577	0.712	**0.811**									
CA	0.635	0.697	0.606	0.646	0.584	0.727	0.716	**0.791**								
SCI	0.498	0.568	0.546	0.524	0.550	0.572	0.596	0.500	**0.789**							
SE	0.547	0.589	0.571	0.674	0.601	0.620	0.620	0.540	0.496	**0.732**						
TTF	0.611	0.665	0.582	0.611	0.585	0.649	0.540	0.536	0.622	0.561	**0.898**					
AU	0.596	0.623	0.582	0.695	0.648	0.640	0.523	0.545	0.516	0.630	0.696	**0.789**				
IF	0.619	0.674	0.624	0.654	0.648	0.732	0.656	0.631	0.629	0.707	0.656	0.643	**0.923**			
IC	0.606	0.690	0.619	0.645	0.644	0.719	0.644	0.635	0.603	0.654	0.663	0.651	0.839	**0.975**		
SAT	0.667	0.670	0.613	0.675	0.622	0.658	0.576	0.641	0.543	0.618	0.762	0.672	0.738	0.703	**0.952**	
PI	0.667	0.751	0.621	0.710	0.639	0.695	0.633	0.611	0.614	0.694	0.780	0.715	0.765	0.777	0.814	**0.973**

The bold value indicates the Fornell-Lacker value.

TABLE 6 Goodness of fit model.

	Chi-square	NCS—X^2/df	RMSEA	CFI	*df*	*p*
Model 1 second order	2288.52	2.167	0.075	0.978	1,058	0.000
Model 2 first order	1375.33	2.784	0.099	0.969	458	0.000

carried out with CFA second order. This study's constructs of course quality, student factor, e-learning tech, overall quality, and student engagement are multidimensional, so they must be measured using a second-order procedure. While the constructs of institutional factors, instructor characteristics, satisfaction, and performance impact are unidimensional, so they must be measured using a first-order procedure.

Reliability testing for all constructs in the theoretical model, both second order and first order, resulted in a CR value of more than 0.7. It means that every dimension and indicator of each measured construct can reflect the primary construct well. In other words, the questionnaire used has a high level of consistency. Likewise, for validity testing, all indicators and dimensions of the primary constructs produce standardized loading factor and AVE values of more than 0.5. It means that each dimension and indicator can reflect its primary construct. In conclusion, the questionnaire used in this study resulted in a high level of validity and reliability. In other word, examination of the correlations between the various factors shows that the factors are highly correlated. The standardized loading factors (SLF) coefficient between the tested factors and items shows that no loading factor value is lower than the bad loading factor limit.

Discriminant validity

Discriminant validity is a concept that means that the two concepts are conceptually different and show a sufficient difference. The point is that a combined set of indicators is not expected to be unidimensional. The discriminant validity test in this study used the Fornell-Lacker criteria. The Fornell-Larcker postulate states that a latent variable shares more variance with the underlying indicator than other latent variables. It means that if interpreted statistically, the AVE value of each latent variable must be greater than the highest r^2-value with the value of the other latent variables (Henseler et al., 2015). **Table 5** presents information that the AVE root value for each variable is greater than the correlation of other variables. So that discriminant validity is fulfilled correctly.

This study also measures the level of goodness of the theoretical model as measured by chi-square, NCS, RMSEA, and NFI statistics. Since chi-square is too sensitive to sample size (Hair et al., 2019), the chi-square ratio approach to degrees of freedom (χ^2/df— NCS) was applied. The NCS value is less than 3, meaning that the model fit is acceptable (Hair et al., 2019). Next is the CFI. The results are presented in **Table 6** and **Figure 2**. In the first model, overall quality, course quality, student factor, student engagement, and e-learning technology,

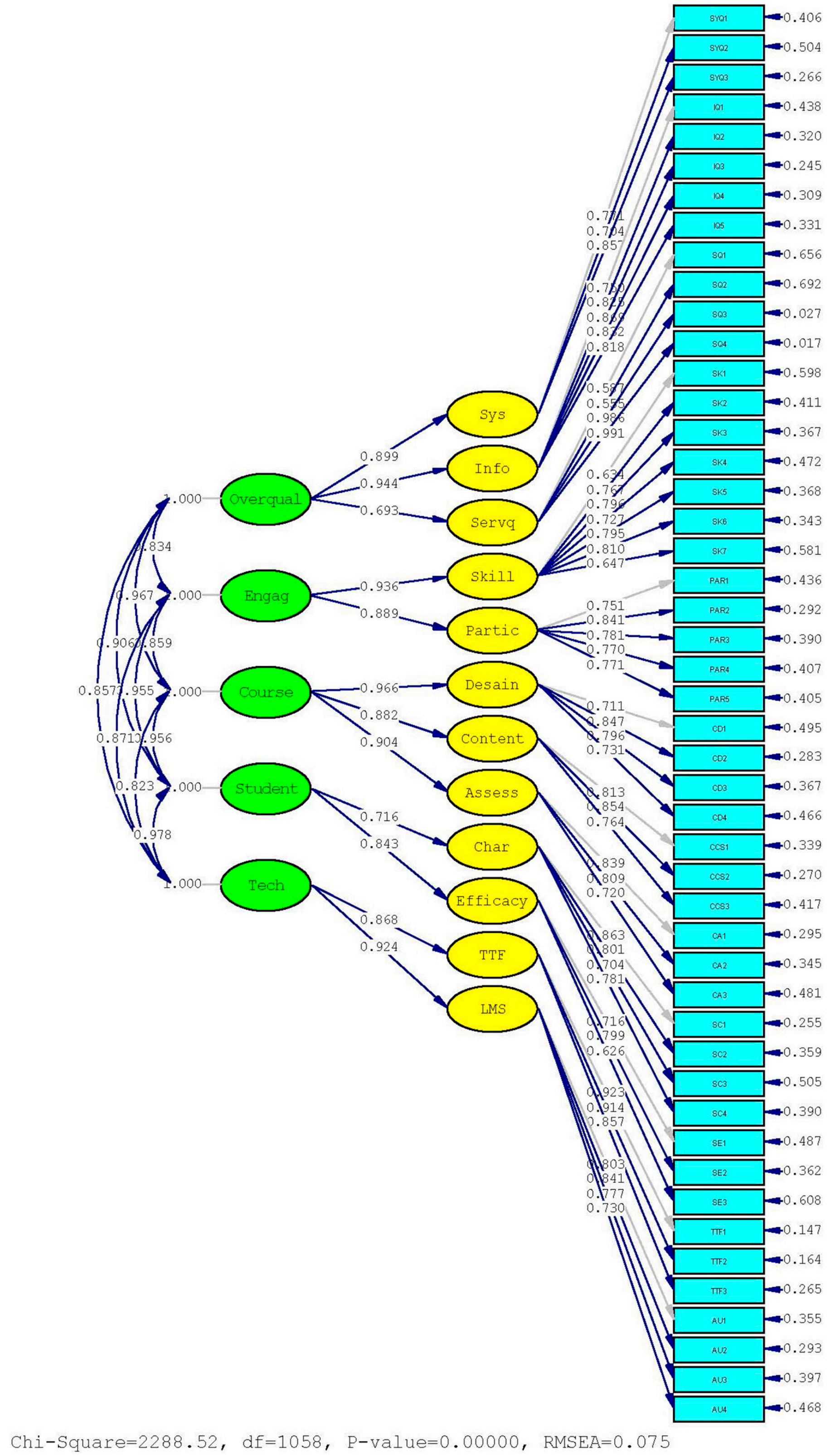

FIGURE 2
Validity and reliability (second order).

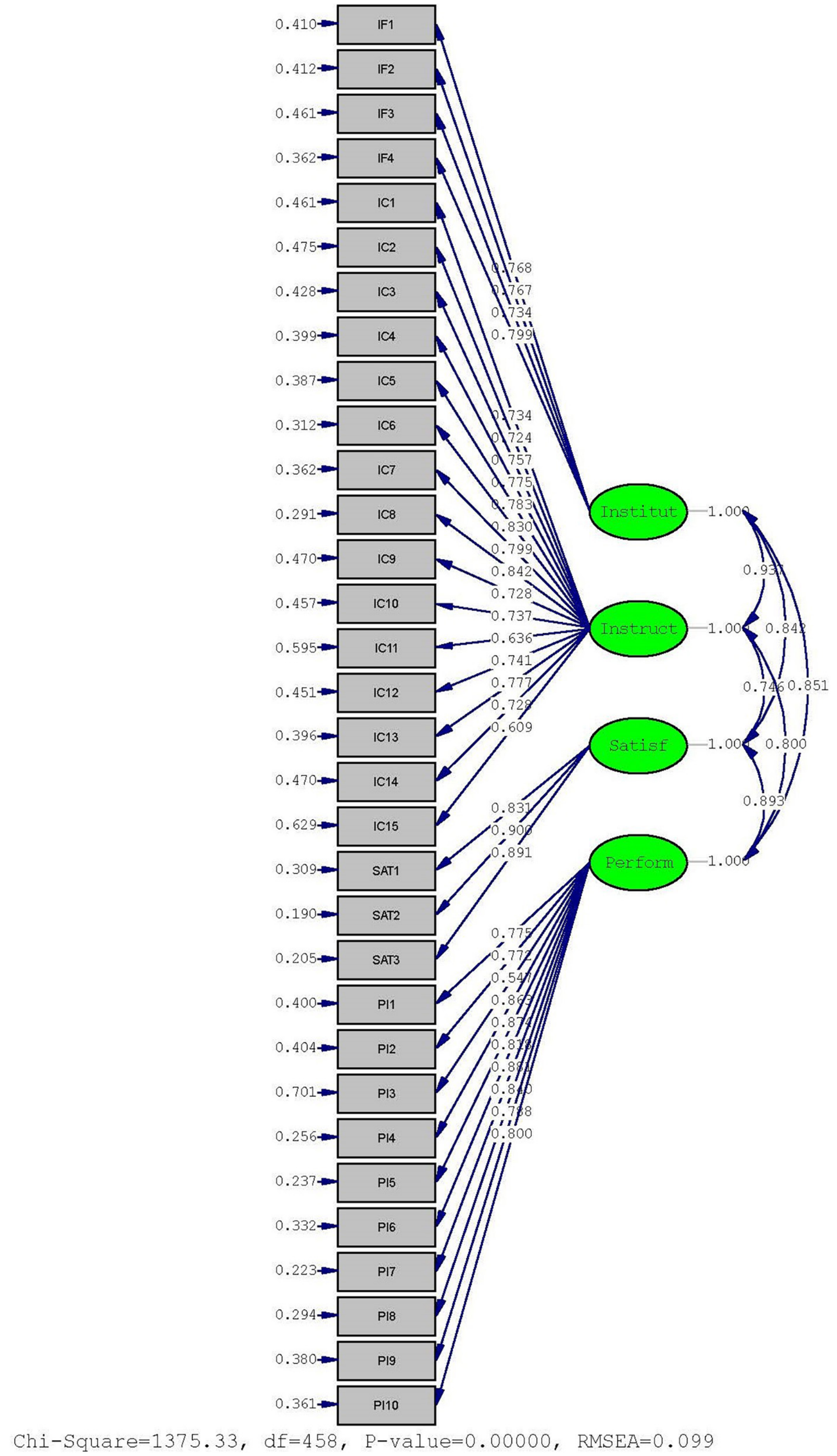

FIGURE 3
Validity and reliability (first order).

as measured by the second-order model, resulted in a Chi-Square value (X^2 = 2288.520, p 0.000 $<$ 0.05), which indicates the model is not good. However, the NCS value of the theoretical model indicates model fit (NCS = 2.167 $<$ 3), and the RMSEA value (0.075 $<$ 0.08) indicates the theoretical model fits the population covariance matrix. Because the RMSEA and NCS values meet the model goodness requirements, they support a reasonable fit between the theoretical model and the data. CFI is also used to determine whether the model is sound and fits the data. CFI compares the fit of the theoretical model or the model under test with the independence model in which all latent variables are uncorrelated. In the results of this study, the CFI value of 0.978 is greater than 0.90, so it can be concluded that the model is fit.

The second model measured by first order is institutional factors, instructor characteristics, satisfaction, and performance impact (**Figure 3**). As a result, the first order model shows a poor data fit (χ^2 = 1375.33; χ^2/df = 2.784; CFI = 0.969; RMSEA = 0.099). The results of the validity and reliability model for the first order, the RMSE value of 0.099 $>$ 0.08, are considered that the measurement model does not meet the fit criteria. However, other researchers state that RMSEA $<$ 0.10 is still considered fit but poor (Singh et al., 2020). In addition, the NCS value of 2.784 $<$ 3 and the CFI of 0.968 $>$ 0.90 is considered to meet the model's goodness.

Discussion and implication

This study aims to propose a conceptual framework for measuring the impact of student performance in online learning on a sample of students from various study programs. Because the learning models in social and technical studies programs are different, measuring the two groups of samples is necessary. This study offers an instrument in the concept of online learning that focuses on measuring student perceptions of course quality, student engagement, e-learning technology, overall quality, student factors, institutional factors, instructor characteristics, and satisfaction that impact student performance. The results of the study prove that the measurement of instrument course quality, student engagement, e-learning technology, overall quality, and student factors on a second-order basis produces good validity and reliability values with the support of model fit. While the instrument measurements on instructor characteristics, institutional factors, satisfaction, and performance impact, though they produced good validity and reliability values, the model's fit was not satisfactory. In particular, the Lisrel program provides instructions for modifying the refinement of the model by relating the covariate errors to the instructor characteristics and performance impact factors because it produces an RMSEA value that does not fit. However, because this study is an initial finding, treatment is not carried out by relating the covariate error (Hulland et al., 2018; Hair et al., 2019).

Generally, this study provides information that most students respond positively to all constructs. It can be interpreted that students who attend lectures using the online learning method view all exogenous constructs as essential to improving their performance. Our results align with previous literature, which explains that the performance of students participating in online learning programs is still less than optimal (Kim et al., 2021), and there are still students who are unwilling to continue their studies (Xavier and Meneses, 2021). Students are unfamiliar with online learning systems and are used to traditional pedagogical styles (Maheshwari, 2021). In addition, internet access is still low compared to developed countries because infrastructure is still not well developed in Indonesia.

Conclusion, limitation, and future research

This study concludes that the model for measuring student learning performance in universities that implement online learning systems is acceptable. The results of this study contribute to universities and educators improving the performance of student learning outcomes. This model will guide them in achieving practical national education goals or help them improve the current system. From the educator's view, it helps make plans for teaching materials that are effective and follow students' needs. For universities, providing input to improve the online learning system that is currently running so that it can produce graduates who can compete in the world of work.

This study has several limitations, such as the lack of sample size, which impacts the value of the model's fit. In addition, this study does not distinguish the validity and reliability of results between social and engineering studies programs. Therefore, for further research, it is possible to add a larger number of samples to provide more comprehensive results and distinguish the validity and reliability of students from social studies and engineering programs. It is because the courses are different. In addition, to test the hypothesis on the proposed conceptual model, it is possible to distinguish students' level of performance in social studies and engineering programs using the multigroup analysis method.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HP, RI, and YY contributed to the conception and design of the study, wrote the first draft of the manuscript, conceptual framework, and literature review. RI organized the database and performed the statistical analysis. All authors contributed to the manuscript revision, read, and approved the submitted version.

Funding

This work was supported by "Model Evaluasi Pembelajaran Daring Dalam Menilai Kualitas Sistem Pendidikan Tinggi Di Indonesia" (contract number: 3481/LL3/KR/2021 and contract date: 12 July 2021).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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