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Research article

Student Satisfaction with Online Learning: A Multigroup Analysis

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ABSTRACT

The Coronavirus disease 2019 pandemic "forced" students to attend online classes roughly from mid-March 2020. This situation, which caused universities, among other institutions, to deal with an overnight change in course delivery from traditional face-to-face to online mode, has resulted in many students facing difficulties. They must cope with the available infrastructure, unstable and limited Internet connection, course delivery, and their self-discipline. Male and female students may have different preferences regarding technology use. This study focused on student satisfaction with the above situation and determined whether a difference exists between male and female students using Technology Acceptance Model as the main theoretical background. Seven hypotheses were proposed and tested with the whole dataset and comparisons between the two groups. Due to the strict health protocol, an online survey was employed using Google Form to collect data. Respondents were 327 undergraduate students from one higher institution in Yogyakarta, comprising 140 male and 187 female students. The population consisted of undergraduate students who have been attending online classes since March 2022. A multigroup analysis was performed using SmartPLS 3.3.3. Results indicated no gender difference in all hypothesized relationships. The theoretical contribution can be seen from the use of Internet Quality, User Interface Quality, and Delivery Quality as the three exogenous variables of the proposed model. The practical contribution is that technology designers must pay attention to the different preferences of user groups.

1. Introduction

The presence of current technology has become an inseparable aspect of various fields of human life. In the world of education, higher education is no exception. Technology has significant influences, such as integrating technology in an education curriculum, technology as a learning medium, and technology as a component of science. Technology use in learning media, for example, e-learning, has increased. Initially, e-learning-based platforms did not allow for interactions via audios or videos, and the number was minimal. Recently, several e-learning platforms can deliver audio–video technology and video conference-based websites, such as Cisco Webex, Zoom, Hangouts Meeting, and Skype.

The Coronavirus disease 2019 (COVID-19) pandemic has made online learning the only option for teaching and learning activities. The COVID-19 outbreak caused all parties, including universities, study programs, lecturers, and even students, to be ready to carry out lectures online. Online learning involves a specific platform and/or a video conference website in which its usage depends on the abilities of lecturers and students to work with that platform. In addition to this unpreparedness, challenges and knowledge of the media used in online lectures influence student involvement in using a specific venue.

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No exhaustive studies about gender differences in online learning have been conducted. From the few research related to gender differences, conflicting results exist about which group, male or female, has greater satisfaction. A study reported that male students have greater satisfaction than female students [1]. Another study revealed that female students are more satisfied than males [2].

Such results are contradicting. Therefore, understanding the factors influencing student satisfaction (SS) with online learning in the shadow of the COVID-19 pandemic, where several aspects of online learning were not well prepared, is interesting. This study aimed to see whether differences exist in the satisfaction of male and female students toward online learning with the background mentioned above.

The rest of the article is presented in the following manner. Section 2 presents the Literature Review and Hypotheses. Section 3 describes the Research Methods, which focus on explaining the survey instruments and data collection, including how the survey was conducted. Section 4 is the Result and Discussion. Section 5 presents the conclusion, which contains study limitations and suggestions for further research.

2. Literature Review and Hypotheses

Online learning involves intensive technology use. In Information Systems, a conceptual model related to technology acceptance exists, i.e., the Technology Acceptance Model (TAM) [3]. Many studies relate online learning to TAM. Ibrahim et al. [4] investigated the intention to use e-learning as the final endogenous variable. They proposed three exogenous variables: course design, instructor characteristic, and computer self-efficacy. They found that computer self-efficacy significantly influences ease of use, positively impacting the intention to use e-learning. To understand the acceptance of distance learning, a study by [5] used an adapted TAM called the General Extended Technology Acceptance Model for E-Learning. This model incorporates four exogenous variables, i.e., student experience, enjoyment, computer anxiety, and self-efficacy. The collected data supported the 14 hypotheses relating the four exogenous variables to TAM variables.

Studies on SS with online learning have been conducted for various purposes. Almusharraf and Khahro [6] evaluated SS with an online learning platform and student experience using transformative learning theories and three independent variables: facility performance, evaluation, and recommendations from other students. They revealed significant relationships among these three independent variables to the overall satisfaction. A research conducted by [7] attempted to understand the factors influencing student learning in a blended course. It reported that enjoyment positively affects SS, whereas anger and boredom negatively affect it. Another study performed by [8] aimed to see gender differences in business simulations. It showed a statistically significant difference between males and females in adopting the simulation strategy.

As previously mentioned, TAM was used as the main theoretical background. Specifically, many studies on technology acceptance or usage behavior employ TAM as their theoretical background. In the original TAM, the final endogenous variable is usage behavior, and the only exogenous variable is perceived ease of use (PEU). TAM does not specifically describe what parts of the technology under consideration can be perceived as easy to use. Researchers choose what is/are considered the antecedent(s) of PEU. Two mediating variables in TAM are attitude toward using and intention to use. Both variables constitute the voluntariness of using or accepting a particular technology. Thus, TAM is appropriate for the voluntary usage of technology under consideration. Students must use the same application their lecturers use in online learning. This situation can be regarded as the mandatory use of a particular online application. Therefore, in this study, two constructs in TAM, i.e., attitude toward using and intention to use, were dropped. In a work related to technology usage, satisfaction is defined as user convenience and a positive attitude toward system use [9]. Satisfied users can spend time on an online learning application, reuse it, and possibly recommend it to friends. Therefore, user satisfaction regarding online learning applications is one of the goals of designing these applications [10]. Bossman and Agyei [11] argued that PEU and perceived usefulness (PU) are two constructs that can be used to predict satisfaction. The present study defined satisfaction as user comfort and positive attitude toward using online learning applications.

Perception is a process of organizing, identifying, and interpreting sensory information to represent and understand the presented information or environment [12]. Perceptions of any issue,

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object, or individual shape people's ways of thinking, opinions, and future views. Thus, students' perceptions of online learning show their thoughts, beliefs, and views on online learning, influencing them to use it [13]. Their study showed that most respondents have positive perceptions of online learning. Another interesting point is a positive correlation between positive perceptions of online learning and academic performance. This result is also in line with [14], a survey that conveyed several keywords, including the usefulness of online learning, student motivation, better understating of course material, and cost-effectiveness. The negative sides of online learning are mainly due to limitations or no Internet access.

Researchers have also explored online learning. Kozlova and Pikhart [15] argued that students' perceptions of online learning technology are closely related to their experiences (perceived experiences) and their areas of expertise. Good experience with technology use brings out specific skills. The study by [16] specifically observed the teaching and learning process dimensions. It indicated that feedback and evaluations of student activities and assignments positively affect SS. Similarly, flexibility and the suitability of learning material delivery positively affect SS. Students' perceptions of online learning can also be seen from their engagement in using online learning applications. Santosa [17] observed the factors that directly or indirectly influence student engagement with online learning applications. It showed that prior knowledge indirectly affects student involvement with online learning applications. On the basis of the mentioned previous studies, the following hypotheses are proposed:

Hypothesis 1 (H1): The effect of Internet Quality (IQ) on PEU is the same in both groups.
Hypothesis 2 (H2): The effect of User Interface Quality (UIQ) on PEU is the same in both groups.
Hypothesis 3 (H3): The effect of Delivery Quality (DQ) on PEU is the same in both groups.
Hypothesis 4 (H4): The effect of DQ on PU is the same in both groups.
Hypothesis 5 (H5): The effect of PEU on PU is the same in both groups.
Hypothesis 6 (H6): The effect of PEU on SS is the same in both groups.
Hypothesis 7 (H7): The effect of PU on SS is the same in both groups.

The seven hypotheses are presented as a path model, as shown in Fig. 1.

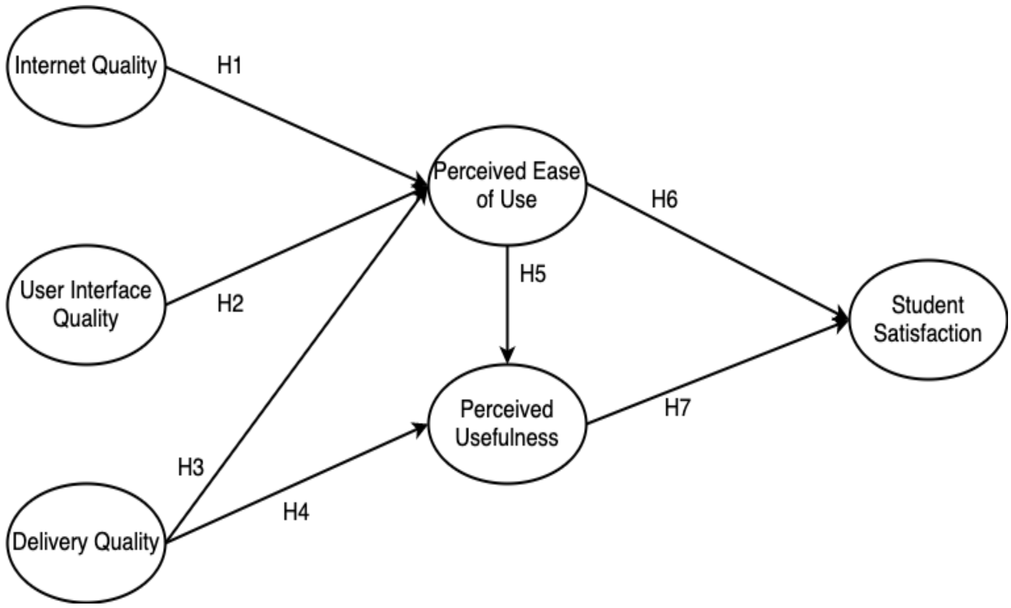

Fig. 1. Path model of the hypotheses

3. Methods

The study is quantitative in nature, namely, a survey is conducted. This section describes the operational definitions of variables, questionnaires, and data collection, complete with an explanation of the population and the number of respondents who took part in the survey.

3.1. Variable Operationalization

Before questionnaires were developed, all variables needed to be operationalized. Such operationalization is as follows:

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- IQ: Level of respondents' perceptions of the Internet accessibility used to participate in online learning
- UIQ: Level of respondents' perceptions of whether the online learning application interface is good
- DQ: Level of respondents' perceptions about the appropriateness of the delivery of materials carried out by lecturers who teach subjects
- PEU: Level of respondents' perceptions of how easy the application is to operate
- PU: Level of respondents' perceptions of how practical the application used in online learning
- SS: Level of respondents' perceptions of their satisfaction with online learning carried out using specific applications

3.2. Instrument

Based on the variable operationalization explained in Section 3.1, several indicators for every variable were defined. Overall, IQ, UIQ, DQ, PEU, PU, and SS were measured using five, seven, four, five, four, and six indicators, respectively. All indicators were measured using a five-point Likert scale. Table 1 presents the questionnaires used in this study.

Table 1. Questionnaires

Latent Variable	Indicator	Questionnaire
IQ	IQual1	The Internet facility was adequate.
	IQual2	The Internet infrastructure was good.
	IQual3	The Internet bandwidth was complete.
	IQual4	The Internet connection was never broken down.
	IQual5	The Internet connection was always available.
UIQ	UIQual1	The application has an attractive interface.
	UIQual2	The application has an exciting interface.
	UIQual3	The application has an intuitive interface.
	UIQual4	The application has an informative interface.
	UIQual5	The application has an easy to remember interface.
	UIQual6	The application has an easy to learn interface.
	UIQual7	The application has suitable metaphorical icons.
DQ	DelQual1	I think the course material was delivered in a fun way.
	DelQual2	I think the course material was delivered appropriately.
	DelQual3	I think the course material was delivered creatively.
	DelQual4	I think the course material was delivered interactively.
PEU	PEU1	I feel that the application was easy to use.
	PEU2	I feel that the application was easy to operate.
	PEU3	I feel that the application was easy to learn.
	PEU4	I feel that the application was easy to manage.
	PEU5	I feel that the application was flexible.
PU	PU1	I feel that the application was suitable for file sharing.
	PU2	I feel that the application was suitable for discussion.
	PU3	I feel that the application was suitable for consultation.
	PU4	I feel that the application was suitable for collaboration.
SS	SS1	I get more benefits from online learning.
	SS2	I feel satisfied with online learning.
	SS3	I feel happy with online learning.
	SS4	I feel comfortable with online learning.
	SS5	I have had a positive experience with online learning.
	SS6	I feel happy with the online learning I attended.

3.3. Data Collection

Data collection for testing the hypotheses was carried out using a survey. Due to the COVID-19 pandemic, the survey was conducted online using Google Form. The population comprised undergraduate students from one higher institution in the region who, since mid-March 2020, have been attending online classes. Respondents participated voluntarily after an announcement regarding this

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survey was spread via several social media, especially WhatsApp. A total of 327 responses were obtained, consisting of 140 male students and 187 female students. All responses were complete; thus, they were used for data analysis directly. One of the risks in a survey is the emergence of a common bias method (CMB). To reduce CMB, all indicators related to one variable were not placed in one group, but randomly.

4. Results and Discussion

Data analysis, including the multigroup analysis, was performed using SmartPLS 3.3.3 [18]. It was also carried out using the structural equation modeling (SEM) because the path model, which is a visualization of all proposed hypotheses, contains mediator variables that make the model more complex than the model without mediators. Using the SEM model, the calculations of the relevant parameters are carried out simultaneously in one execution compared with the analysis of the non-SEM model, which must be carried out part by part. In addition, in SmartPLS, the analysis is directly performed from the path model graph.

SmartPLS, a version of partial least squares–structural equation modeling (PLS–SEM), is a nonparametric statistical method. Nonparametric statistical methods do not require that data follow a normal distribution. Covariance-based SEM (CB-SEM), which applies maximum likelihood, is a parametric statistical method and thus requires data to follow a normal distribution [19]. In addition, PLS–SEM is primarily used for exploratory studies, whereas CB-SEM is mainly used for confirmatory analysis [20]. This study is an exploratory; thus, PLS–SEM is appropriate.

Data analysis using SmartPLS comprises two steps: measurement model or outer model and path model (inner model). Given that this study aimed to understand gender differences, another step was conducted, i.e., multigroup analysis.

4.1. Measurement Model (Outer Model) Assessment

The measurement or outer model relates to the validity and reliability of the instrument used in this study. It focuses on each latent variable and its corresponding indicators. The instrument validity and reliability can be checked through loading, composite reliability, average variance extracted (AVE), and cross-loading. Loading is the contribution of each indicator to its corresponding latent variable. It has a minimum value of 0.70 [21]. Otherwise, it must be dropped from the model because it is unreliable. In the first iteration of the path model depicted in Fig. 1, two indicators were dropped from the model because their loading scores were less than 0.70. These indicators were IQual4 and PU1. In the second iteration, all indicators had their scores >=0.70; thus, they were used for further analysis.

Composite reliability (construct reliability) is a measure of internal consistency reliability. This measure is often compared with Cronbach's alpha, although they are not the same. According to [19], the internal consistency score must be >=0.7, but for exploratory research, the score between 0.60–0.70 is considered acceptable. Table 2 shows the construct reliability and validity for the complete dataset (Column C), male group dataset (Column M), and female group dataset (Column F).

Table 2. Construct reliability and validity

Construct	Cronbach's Alpha			Composite Reliability			AVE		
	C	M	F	C	M	F	C	M	F
IQ	0.866	0.879	0,857	0.909	0.917	0,903	0.715	0.734	0,703
UIQ	0.918	0.916	0,92	0.934	0.933	0,935	0.670	0.667	0,675
DQ	0.837	0.867	0,806	0.890	0.909	0,872	0.670	0.714	0,631
PEU	0.966	0.967	0,965	0.974	0.975	0,973	0.881	0.884	0,879
PU	0.897	0.906	0,89	0.935	0.941	0,931	0.828	0.842	0,819
SS	0.934	0.942	0,927	0.948	0.954	0,942	0.752	0.776	0,732

Table 2 presents that all indicators are deemed suitable at the indicator level. Discriminant validity can be checked at the construct level using cross-loading and the Fornell–Larcker criterion. Cross-loading is an indicator's correlation with other constructs in the model. An indicator should only

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correlate with the latent variable it represents. In practice, the indicator of one latent variable can correlate with other latent variables. Cross-loading ensures that the correlation between the indicator and the latent variable it represents must be greater than the correlation between the indicator and other latent variables. Table 3 shows that cross-loadings are all good, as indicated by the shaded cells.

The Fornell–Larcker criterion [22] compares the square root AVE of a latent variable and the correlation coefficient of that latent variable with other latent variables. According to this criterion, if the value of squared-root AVE is greater than the correlation coefficient, then this latent variable fulfills such a criterion at the construct level. Table 4 displays the results of the Fornell–Larcker criterion calculation. Based on these results, especially the shaded cells, the discriminant validity at the construct level is deemed suitable.

Table 3. Cross-loading indicators for the complete dataset

Indicator	IQ	UIQ	DQ	PEU	PU	SS
IQual1	0.868	0.510	0.395	0.574	0.414	0.332
IQual2	0.896	0.562	0.332	0.706	0.379	0.321
IQual3	0.731	0.393	0.270	0.455	0.329	0.299
IQual5	0.878	0.492	0.361	0.612	0.427	0.381
UIQual1	0.432	0.839	0.512	0.511	0.410	0.396
UIQual2	0.467	0.796	0.526	0.481	0.416	0.416
UIQual3	0.449	0.843	0.491	0.485	0.357	0.388
UIQual4	0.473	0.855	0.506	0.522	0.390	0.429
UIQual5	0.493	0.815	0.376	0.556	0.382	0.334
UIQual6	0.520	0.797	0.405	0.597	0.363	0.350
UIQual7	0.506	0.784	0.386	0.503	0.327	0.227
DelQual1	0.289	0.451	0.823	0.365	0.437	0.541
DelQual2	0.385	0.453	0.810	0.469	0.427	0.498
DelQual3	0.374	0.506	0.875	0.408	0.427	0.562
DelQual4	0.248	0.400	0.763	0.305	0.316	0.413
PEU1	0.666	0.581	0.469	0.948	0.483	0.385
PEU2	0.675	0.600	0.475	0.956	0.504	0.407
PEU3	0.658	0.606	0.456	0.945	0.533	0.385
PEU4	0.668	0.604	0.422	0.943	0.518	0.369
PEU5	0.637	0.618	0.429	0.901	0.545	0.423
PU2	0.385	0.413	0.424	0.473	0.889	0.345
PU3	0.421	0.402	0.482	0.500	0.918	0.461
PU4	0.442	0.446	0.446	0.529	0.923	0.434
SS1	0.357	0.420	0.553	0.380	0.426	0.850
SS2	0.383	0.419	0.530	0.358	0.362	0.823
SS3	0.346	0.381	0.544	0.355	0.413	0.906
SS4	0.327	0.324	0.484	0.337	0.403	0.877
SS5	0.318	0.381	0.563	0.393	0.419	0.868
SS6	0.314	0.375	0.549	0.358	0.346	0.877

Table 4. Fornell–Larcker criterion for the complete dataset

	IQ	UIQ	DQ	PEU	PU	SS
IQ	0.846	0.585	0.403	0.704	0.458	0.393
UIQ	0.585	0.819	0.556	0.642	0.462	0.443
DQ	0.403	0.556	0.819	0.480	0.496	0.620
PEU	0.704	0.642	0.480	0.939	0.551	0.420
PU	0.458	0.462	0.496	0.551	0.910	0.457
SS	0.393	0.443	0.620	0.420	0.457	0.867

4.2. Path Model (Inner Model) Assessment

Path model assessment deals with hypothesis tests. It comprises the path coefficient (***β***) and the significant level obtained from calculating the collected data. These two parameters are combined to

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either accept or reject the hypotheses. In SmartPLS, path coefficient calculation is performed together with measurement model assessment.

The significant level calculation is conducted by running the bootstrapping algorithm. This study used the significant level =0.05 ($\alpha = 0.05$). Table 5 summarizes the path coefficient between two variables, as stated in the hypotheses and its corresponding *t*-value and *p*-value. Given that this study aimed to see whether a gender difference exists in each relationship between the two variables, Table 5 also depicts path coefficients and their corresponding significant levels for male and female groups. Moreover, it shows that the overall and individual group datasets support all hypothesized relationships.

Table 5. Comparison of the path coefficients for three different datasets

	Complete Dataset			Male Group Dataset			Female Group Dataset		
	β	*t*-value	*p*-value	β	*t*-value	*p*-value	β	*t*-value	*p*-value
IQ → PEU	0.486	8.540	0.000	0.478	5.177	0.000	0.498	7.564	0.000
UIQ → PEU	0.289	4.628	0.000	0.331	3.610	0.000	0.244	2.798	0.003
DQ → PEU	0.123	3.037	0.003	0.099	1.811	0.035	0.152	2.327	0.010
DQ → PU	0.301	6.416	0.000	0.275	3.727	0.000	0.337	5.095	0.000
PEU → PU	0.406	6.766	0.000	0.426	4.659	0.000	0.387	5.196	0.000
PEU → SS	0.241	3.409	0.001	0.299	3.618	0.000	0.174	1.805	0.036
PU → SS	0.325	4.994	0.000	0.397	5.074	0.000	0.284	2.990	0.001

The model's goodness of fit can be seen from the coefficient of determination or R^2 of the endogenous variables. Table 6 shows the R^2 in two forms: the original and adjusted scores. Based on the R^2 adjusted score, all other variables in the model explain 24.5% of the variance of SS.

Table 6. Coefficient of the determination of endogenous variables

Endogenous Variable	R^2 (original)	R^2 (adjusted)
PEU	0.587	0.583
PU	0.373	0.369
SS	0.250	0.245

Fig. 2 illustrates a graphical representation of the path or inner model analysis results. As explained in Section 3.1, two indicators, i.e., IQual4 and PU1, were omitted in the analysis because their loading values were less than 0.7.

4.3. Multigroup Analysis

A multigroup analysis was conducted to test whether the difference in each path coefficient value between male and female groups was significant. Before the multigroup examination, an invariant test was performed using MICOM to test whether the two groups were invariant. Table 7 presents the result of MICOM that shows full invariance between male and female groups.

Specifically, multigroup analysis was performed using SmartPLS 3.3.3. Based on the path coefficients for male and female groups, Table 8 presents the difference between each pair of path coefficients for the two groups and their corresponding *p*-values. The *p*-value column shows that all differences in path coefficients are greater than the value of $\alpha = 0.05$. Thus, statistically, no difference in path coefficient score was found between male and female groups.

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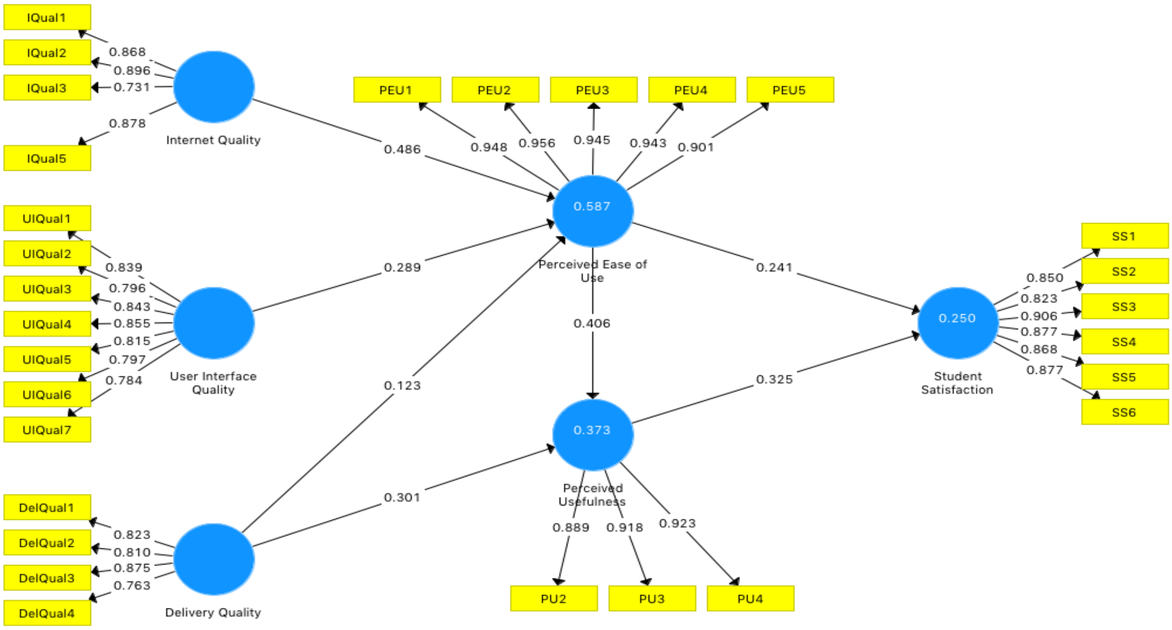

Fig. 2. Graphical representation of the path/or inner model analysis results for the complete dataset

Table 7. Measurement invariance test using MICOM

Construct	Correlation Value	5% Quantile Value	Compositional Invariance
IQ	0.999	0.998	Yes
UIQ	0.999	0.997	Yes
DQ	0.999	0.994	Yes
PEU	1.000	1.000	Yes
PU	1.000	0.999	Yes
SS	0.999	0.999	Yes
Construct	**Mean Original Difference**	**95% Confidence Interval (CI)**	**Equal Mean Value**
IQ	0.059	[−0.237, 0,213]	Yes
UIQ	−0.024	[−0.218, 0,229]	Yes
DQ	0.010	[−0.207, 0,207]	Yes
PEU	−0.122	[−0.229, 0,218]	Yes
PU	0.042	[−0.231, 0,221]	Yes
SS	−0.099	[−0.213, 0,223]	Yes
Construct	**Variance Original Difference**	**95% CI**	**Equal Variance**
IQ	0.301	[−0.391, 0,349]	Yes
UIQ	0.258	[−0.465, 0,423]	Yes
DQ	0.302	[−0.507, 0,460]	Yes
PEU	0.229	[−0.443, 0,414]	Yes
PU	0.110	[−0.353, 0,319]	Yes
SS	0.182	[−0.365, 0,312]	Yes

Table 8. Path coefficient differences and their corresponding *p*-values ($\alpha = 0.05$)

Hypothesis	M-Group (β_M)	F-Group (β_F)	Difference (β_M-β_F)	*p*-values	Hypothesis Test
H1: IQ → PEU	0.478	0.498	−0.020	0.564	Accepted
H2: UIQ → PEU	0.331	0.244	0.087	0.258	Accepted
H3: DQ → PEU	0.099	0.152	−0.053	0.734	Accepted
H4: DQ →PU	0.275	0.337	−0.062	0.746	Accepted
H5: PEU → PU	0.426	0.387	0.039	0.372	Accepted
H6: PEU → SS	0.299	0.174	0.125	0.181	Accepted
H7: PU → SS	0.397	0.284	0.113	0.179	Accepted

M-Group: male group, F-Group: female group

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This article reports survey results to measure SS with online learning and determines whether differences exist between male and female groups. The path model uses PEU and PU as mediators. The independent variables are IQ, UIQ, and DQ.

Based on the results obtained from the path model assessment, all relationships between pairs of variables stated in the hypotheses and shown in Fig. 1 have significant path coefficients. For example, referring to Table 5, IQ significantly affects PEU for all datasets. This significant effect can be seen from the *p*-value, smaller than $\alpha = 0.05$. The rest of the relationships also have the same notions.

Table 5 presents the differences in path coefficients between male and female groups. However, from the significance test results shown in Table 8, the differences are proven insignificant. That is, no difference in path coefficient exists between male and female groups. Therefore, no difference exists in satisfaction with online learning between these two groups.

The main finding in which no gender difference is found between male and female SS contradicts [1] where male students have greater satisfaction than female students and vice versa [2]. This contradiction may be caused by different online learning settings, differences in exogenous variables or other things that deserve further exploration. Differences in exogenous variables are understandable because of differences in interest and research focus.

The independent variables used in this study are IQ, UIQ, and DQ. The first two independent variables explain the infrastructure needed to carry out online learning. Hypothesis test results indicate that these two variables affect PEU and PU. These results imply that students have no problem accessing the provided online learning infrastructure.

The third independent variable is DQ, which is defined as a student's perception of how a lecturer delivers a course. This study employs four indicators to measure DQ: fun, appropriateness, creativity, and interactivity. Overall, the combined four indicators positively influence ease of use and usefulness. This finding suggests that an exciting and creative way of delivering a course material encourages students to take advantage of their online learning activities. This encouragement causes positive perceptions of ease of use and usefulness of an online application. Even though the learning is carried out online, the quality of delivering a course is also an essential factor for the success of the online teaching and learning process.

Moreover, two constructs of TAM, i.e., PEU and PU are used. In the complete TAM model, the antecedents of PEU are external variables related to the technology under study. In this research, the two antecedents of PEU are IQ and UIQ of the online learning application used. Another variable, namely, DQ, which is operationalized as "the appropriateness of a delivery material," can be related to the use of a tool for the delivery of a course material. The addition of one exogenous variable expands the TAM model. Thus, the theoretical contribution of this research is adding DQ as an antecedent of PEU.

The finding provides a practical implication, i.e., course instructors must deliver learning materials in an engaging, enjoyable, and creative manner. Unlike the face-to-face learning mode where most lecturers find conveying interesting, fun, and creative lectures easy, other lecturers are unprepared to do so in online learning. Most lecturers do not have experience delivering online lectures where they practically deal with computer screens. This situation implies the need for training to make them further accustomed to delivering courses online.

The e-learning technology, which is the background of this study, is widely available. As one of the technology acceptance models, TAM is also commonly used in understanding the acceptance of various technologies. Referring to these two points, the proposed model can be applied in many regions. However, differences in student and technology characteristics must also be considered.

5. Conclusion

Due to the COVID-19 pandemic, students must attend online classes despite this learning mode not being planned well. Students and faculties have struggled to cope with the situation. This study is conducted to understand SS with online learning, i.e., course delivery and technical elements manifested as the IQ and UIQ of the online learning application used during online learning. This work does not explicitly refer to one application but to all applications used by students, as directed by their lecturers. The nonspecific application is based on various courses because they are taught by different lecturers and are delivered using multiple applications.

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The collected data support all seven hypotheses. All the hypothesized relationships between latent variables show no difference between male and female students. For example, no difference in the effect of DQ on PEU is found between male and female groups where the difference in their path coefficients =–0.053 and p-value =0.746; no difference in the effect of PU on SS is observed between both groups where the difference in their path coefficients =0.113 and p-value =0.179. Thus, no difference exists between male and female SS with online learning.

The study limitations are mainly because of the selection of exogenous variables, namely, extrinsic variables. On the one hand, according to the theoretical basis, namely, TAM, IQ, and UIQ are appropriate as exogenous variables in the TAM model. On the other hand, satisfaction is not only influenced by extrinsic factors but also by intrinsic factors. Therefore, future research should address intrinsic factors.

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