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VALIDITY ASSESSMENT OF STUDENTS' ACCEPTANCE TOWARDS ONLINE DISTANCE LEARNING

Nur Huda Jaafar[1*], Mohd Hanafi Azman Ong[2], Haslenda Yusop[3], Suhanah Rosnan[4], Zuriati Ismail [5], Mohd Hafizan Musa[6], Rashidah Mokhtar[7]

[1, 2, 3, 4, 5, 6, 7]*College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Cawangan Johor, Kampus Segamat, Johor, Malaysia*

[*]Corresponding Author

Email : [1*]nurhu378@uitm.edu.my, [2] napieong@uitm.edu.my, [3] haslenda381@uitm.edu.my, [4]suhan009@uitm.edu.my, [5]zuria986@uitm.edu.my, [6]mohdh233@uitm.edu.my, [7]rashi271@uitm.edu.my

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ABSTRACT

Online distance learning is getting more popular as one of the approaches for delivering teaching and learning. The student's acceptance of online distance learning should be measured rigorously because it helps to indicate the teaching and learning delivery levels of success. An evaluated and validated instrument to measure students' acceptance of online distance learning is needed for this purpose. To achieve this, Exploratory Factor Analysis (EFA) and Nomology Analysis are used to evaluate and validate students' acceptance of online distance learning instruments. The EFA of this study on 32 items resulted in the construction of seven dimensions: Self-Productivity, Content Productivity, Effort Expectancy, External Influence, Personal Innovativeness, Self-Management Learning, and Behavioural Intention. The correlation analysis indicates that all the bivariate relationships among the components were significantly correlated with at least a 95% confidence level. This result shows that the instrument can be considered valid and reliable and used to measure students' acceptance of online distance learning.

Keywords: Nomology Analysis, Online Distance Learning, Students' acceptance.

1.0 INTRODUCTION

Technologies for teaching and learning have undergone many evolutions to be paralleled with the growth of information technology. The utilization of internet technology to assist individuals in their daily routines has a significant influence on their tendency to embrace and explore the domain of online education and learning. Online distance learning has gone through many improvements; from being simply delivered through the telephone, now we can see more online distance learning platforms such as Google Classroom, YouTube, Microsoft Teams, and Kahoot (Stevanović et al.,2021) use the Internet as a more convenient platform. Moreover, the use of multimedia and interactive elements makes online distance learning more fun. Additionally, certain academic institutions also undertake efforts to develop their online distance learning platform for delivering exemplary instruction and knowledge transfer.

The COVID-19 pandemic that hit the world in the past couple of years has driven many educational institutions to make drastic decisions in enforcing online distance learning as one solution to ensure that teaching and learning are still delivered successfully despite the implementation of lockdown procedures in many countries (Mohtar & Yunus, 2022; Patricia

Aguilera-Hermida, 2020; Qiao et al., 2021). Although many educational institutions had their online learning platforms to be utilised by their students and lecturers before the pandemic, most of these institutions simply used these platforms as a supporting tool for teaching and learning activities. The main medium of teaching and learning is still the face-to-face approach. As a result, when the pandemic hit, both students and lecturers must adapt to this new norm, specifically in teaching and learning delivery and drastically accepting the move from face-to-face mode to online distance learning mode as a main medium.

Measuring students' acceptance of online distance learning is crucial and needed as one of the indicators of educational institutions' success in online distance learning implementation. In this paper, we will analyse the items used to measure students' acceptance of online distance learning. The Exploratory Factor Analysis and Nomology Analysis have been utilised to measure the reliability and validity of the instruments. Questionnaires have been distributed to 250 students from Universiti Teknologi MARA who are taking computer science courses.

We will show the literature review of this study in the next section followed by the research methodology. Finally, the discussion of the analysis result is presented before we conclude the paper in the final section.

2.0 LITERATURE REVIEW

2.1 Online Distance Learning

Since the COVID-19 pandemic hit the world, all educational sectors have tried to solve the issue with the help of technology. Online distance learning is a method of delivering teaching content and making the students able to learn. According to Stevanović et al. (2021), distance learning was once performed using the telephone for communication and post to provide the printed teaching material. As the technology evolved, they started recording videos and distributing them together with printed materials. Recent development shows that online distance learning which is based on modern technology and the internet has become the primary method of teaching (Stevanović et al., 2021). The current situation, especially during the COVID-19 pandemic, shows that the use of modern technology and the internet helps a lot of students, lecturers, and education institutions solve the problem of teaching and learning delivery. The teaching and learning activities can be done anytime and anywhere through the use of current technology and the internet.

According to Haningsih and Rohmi (2022), online learning can be described as a learning experience using internet devices where the students can learn from any location whether it is in synchronous or asynchronous mode. Thus, online distance learning can be defined as every phase in the teaching and learning done via the Internet inclusive of the process of sharing materials besides providing communications among students and lecturers. Not only that, but it also includes the way the assessments or exams are being conducted online outside of the classroom (Haningsih & Rohmi, 2022; Stevanović et al., 2021).

There are few opinions from researchers on online distance learning. Firstly, online distance learning must be done to retain the student's learning enthusiasm and their academic performance (Stevanović et al., 2021). According to Rahim et al. (2020), online distance learning has gained a positive impact and helps in developing the student's creative thinking as well as their learning enthusiasm. It also improves the learning interactivity levels between the lecturers and students (Ikhsan et al., 2019). On top of that, it can help to facilitate the learning space and time flexibility. Pinchbeck and Heaney (2022) stated that the demand for online learning had increased during the pandemic due to study and schedule flexibility. In addition, the lecturers can update the learning content anytime within their capacity through online learning. The transition from traditional learning to online learning in higher education helps the university to ensure the educational process continues by putting a strong emphasis on both students' and lecturers' needs (Huang et al., 2020). Moreover, the factors of familiarity with the modern tools in teaching and learning among the lecturers and students do help in their acceptance of the new approach to teaching and learning. Haningsih and Rohmi (2022) also stated that online distance learning is appropriate because it is easy-going, low-cost, and can be executed.

2.2 The Evolution of Online Distance Learning Technologies

The distance learning method has been implemented for many years. Technologies have played as a main instrumental role in the revolution of distance learning (Bozkurt, 2019; Traxler, 2018). Fig 1 shows the ages and generations that were shaped and determined by the dominant communication technologies adopted by distance learning (Bozkurt, 2019). From this figure, we can see that the era of digital knowledge and network society started in the 3rd age. The growth of internet technology encourages the evolution of online distance learning where many types of online distance learning exist, such as Wiki, MOOC, and various types of online quizzes (Kanwar, 2019; Rajesh, 2015).

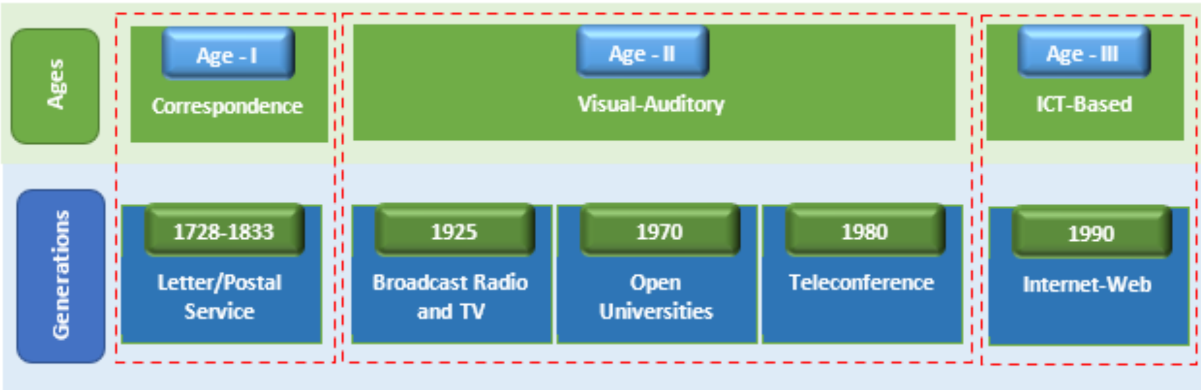

Fig. 1 *Ages and Generation of Distance Learning (Bozkurt, 2019)*

The Industrial Revolution influences the evolution of online distance learning (Kanwar, 2019). In the first industrial revolution, higher education transitioned from being elite to one which anyone could aspire to. Then, in the second industrial revolution, the world focuses on the assembly line and mass production. Indirectly it influences the trend in education where it drives many educational institutions to produce self-instructional booklets and offer correspondence courses. Online distance learning blooms in the third industrial revolution because of the rise of the computer and internet. Then, the fourth industrial revolution is marked by artificial intelligence and robotics development complementing computer and internet technologies. The combination of computer, internet, and artificial intelligence technologies causes the new online distance learning (Elayyan, 2021; Kanwar, 2019).

Besides many MOOC platforms that allow educational institutions to offer free online courses to thousands of students worldwide, artificial intelligence technology is a technology that influences the growth of online distance learning. Intelligent Tutoring Systems, for example, is one of the online distance education technologies that use artificial intelligence techniques to simulate one-to-one human tutoring and provide immediate feedback, all without the presence of the human. Furthermore, artificial intelligence also helps students and lecturers analysing and summarising the discussion in online courses that help human lecturers guide students in collaboration and problem-solving activities (Kanwar, 2019).

2.3 Previous Study on Online Distance Learning

Online distance learning is an alternative that many educational institutions utilise to deliver teaching and learning. The Covid-19 pandemic proves that online distance learning helps both academicians and students in teaching and learning (Mohtar & Yunus, 2022; Patricia Aguilera-Hermida, 2020; Taat & Francis, 2020) despite the movement restrictions. The enforcement by the top management of educational institutions, in the implementation of online distance learning, as a medium for teaching and learning delivery is one of the forces behind both academicians and students adjusting to these changes.

Previous studies show a few factors that affect students' acceptance of any particular teaching and learning technology. Many researchers agree that the students' attitudes are critical factors in accepting a new teaching and learning approach (Durnali et al., 2022; Panigrahi et al., 2018; Patricia Aguilera-Hermida, 2020). Having strong attitudes can drive students' positive behaviour towards the learning medium. With a strong attitude, students have the initiative to identify and use their learning needs, goals, strategies, and resources (Durnali et al., 2022).

In addition, a positive attitude also influences students to be innovative and highly motivated to explore new technologies in the teaching and learning process (Allam et al., 2020). It influences them to be very independent and disciplined in managing their study. Nonetheless, it needs the academicians to give clear directions to ensure the students are still learning and not fall behind during their self-learning sessions.

The effort from academicians to provide complete materials such as notes, tutorials, and solutions will influence students to accept the use of the online distance learning approach (Salloum et al., 2019). The complete content, easy to understand and attractive, can increase acceptance among the students towards the teaching and learning approach. Although the online learning platform is very sophisticated, if the content of materials is poor, then it will decrease the students' acceptance of online distance learning. As a result, academicians need to adapt to new technology in teaching and learning and acquire the skills to deliver efficient content materials (Mokhtar et al., 2020).

3.0 RESEARCH METHODOLOGY

This study uses a combination of cross-sectional and quantitative research designs to evaluate the validity and reliability of the new instruments for measuring students' acceptance of online distance learning. A close-ended questionnaire was designed with 35 items distributed to 250 respondents in this pilot testing stage to determine the variable's structure that exists in these 35 items. A technique of Exploratory Factor Analysis (EFA) was performed by using the Principal Component (PC) algorithm extraction method with the Varimax rotation technique since these techniques can be used as a tool for validity and refinement of items groups used in this study (Creswell, 2014; Hair et al., 2010).

As for ensuring the covariance matrix among the items is sufficient, and not an identity matrix, the Kaiser-Meyer-Olkin (KMO) index should be greater than .60 (Field, 2009) while the Bartlett's Test of Sphericity should be significant (Pallant, 2020), hence the EFA analysis can proceed. Thompson and Daniel (1996) suggested using a multiple-criteria approach for determining the number of factors or variables that should be extracted. In this analysis, only factors with an eigenvalue greater than the Monte-Carlo simulation eigenvalue are taken to be extracted (Hair et al., 2010; Tabachnick & Fidell, 2019). Besides that, the percentage of the variance explained should be more than 60.0% and can be used for determining the numbers factor or variable should be extracted (Hair et al., 2010; Thompson & Daniel, 1996).

In terms of validity of the items, factor loading, and communalities values should be more than 0.50. This value can be considered as the practical value for determining the significant contribution of items towards their respective variable or factor (Hair et al., 2010) since the sample size can be considered as relatively medium large (n = 250). Lastly, an internal test of consistency items grouped from the EFA will be analyzed by using Cronbach's Alpha reliability test. Nunnally (1994) suggested that the cut-off of 0.70 and above can be used to indicate the grouped items are reliable.

To further assess the validity of the extracted factors from the EFA analysis, discriminant and nomological validity was performed. Nomological validity is a logical and relevant relationship that exists among the variables that follow the expected relationship direction, which is either it is a positive or negative relationship (Ong & Mahmud, 2020). In this nomological validity process, correlation analysis was used since this analysis permits the researchers to measure the direction of the relationship among the extracted variables (Creswell, 2014; Field, 2009; Ong & Mahmud, 2020). On the other hand, discriminant validity is about testing the degree to which the measures of different variables are distinct (Hair et al., 2010). Hence, from the correlation analysis, this discriminant validity can be accessed by measuring the strength of the relationship. According to Ong and Mahmud (2020) and Hair et al. (2010), discriminant validity exists when the correlation coefficient is less than .70, which is below moderate strength.

4.0 ANALYSIS

4.1 Validity and Reliability Analysis via Exploratory Factor Analysis and Cronbach's Alpha Analysis

We prepared 35 items in this instrument. The items are stated in Table 1. All items have been tested for validity and reliability analysis. This process is done via Exploratory Factor Analysis and Cronbach's Alpha Analysis.

Table 1. List of Items

Code	***Item***
Q1	I find ODL useful for my studies.
Q2	The ODL enables me to understand the subject contents more quickly.
Q3	The ODL improves my collaboration with my classmates.
Q4	The ODL increases my learning productivity.
Q5	The ODL improves my performance in my studies.
Q6	The notes and examples uploaded on the ODL platforms such as MS Teams and YouTube helped me a lot in improving my studies performance.
Q7	The notes and examples that were uploaded on the ODL platform helped me a lot in understanding my studies.
Q8	The solution of tutorials that were uploaded on the ODL platform helped me a lot in understanding my studies.
Q9	Clear directions and answers that are delivered by my lecturers through the ODL platforms help me to produce quality assignments and outputs.
Q10	The ODL platforms help me to interact with my classmates and lecturers to improve my understanding of my studies.
Q11	I find ODL flexible.
Q12	I find ODL easy to use.
Q13	ODL does not require much effort.
Q14	ODL does not require much time to get used to.
Q15	My interaction in the ODL environment is clear and understandable
Q16	It is easy for me to become skillful in learning in an ODL environment.
Q17	I believe ODL is beneficial if it is recommended to me by my lecturers.
Q18	I believe ODL is beneficial if my lecturers support it.
Q19	I believe ODL is beneficial if my lecturers help me through it.

Code	Item
Q20	I believe ODL is beneficial if the university makes it compulsory.
Q21	I believe ODL is beneficial if the university supports it.
Q22	I believe ODL is beneficial if the university prepares me for it
Q23	I like to experiment with new information technologies
Q24	When I hear about a new information technology, I look forward to examining it.
Q25	Among my colleagues, I am usually the first to try out a technology innovation.
Q26	When it comes to learning and studying, I am a self-directed person.
Q27	In my studies, I am self-disciplined and find it easy to set aside reading and homework time.
Q28	I can manage my study time effectively and easily complete assignments on time.
Q29	In my studies, I set goals and have a high degree of initiative.
Q30	I plan to use ODL to support face-to-face learning.
Q31	If I had a choice, I would prefer ODL over face-to-face learning.
Q32	I predict that I will use the ODL platforms frequently.
Q33	I intend to increase the usage of ODL platforms in the future.
Q34	I will enjoy using the ODL platforms.
Q35	I would recommend others to use the ODL platform as a learning support.

To determine the sufficient number of variables to be extracted, Table 2 shows the summary result of the initial eigenvalue, Monte-Carlo simulation eigenvalues, and cumulative percentage of variance extracted from the EFA analysis. The analysis indicated that seven variables are sufficient enough to be extracted out of the 32 items because the first seven of the initial eigenvalues (18.866, 2.139, 1.440, 1.340, 1.183, 1.056, and 0.987) are greater than the first seven of the Monte-Carlo simulation eigenvalues. Besides that, these seven extracted variables also exceeded 60% of the cumulative percentage of variance explained (Cumulative percentage of variance explained: 83.13%). Therefore, based on this result, from the 32 items, seven variables' items should be extracted.

Table 2. The Summary Result of Multiple Criteria for Group Variables to be Extracted

Component Number	Initial Eigenvalue	Monte-Carlo Simulation Eigenvalue	Cumulative % Variance Explained	Decision
1	18.866	2.158	16.59	Sufficient to extract
2	2.139	1.698	30.80	Sufficient to extract
3	1.440	1.296	44.13	Sufficient to extract
4	1.340	1.204	56.91	Sufficient to extract
5	1.183	1.098	69.27	Sufficient to extract
6	1.056	0.946	76.36	Sufficient to extract
7	0.987	0.836	83.13	Sufficient to extract
8	0.588	0.674	-	Insufficient to extract

Note: Only the first 8 out of 32 components are reported

Table 3 shows the summary result of the EFA analysis for these 32 items using the combination of the Principal Component (PC) extraction technique with the Varimax rotation technique. The KMO index for this analysis was 0.958 with the highly significant result of Bartlett's Test of Sphericity of these data sets ($X^2(496) = 9202.92$, $p < 0.01$). Hence, the data covariance for these 32 items can be considered not an identity matrix and allow the next procedure of the EFA analysis.

The result of the EFA analysis (Table 3) also indicates that all items exceeded the minimum threshold value of 0.50 for both values of factor loading and commonalities. However, to reach this conclusion, three items which are Q1, Q10, and Q17 were removed one by one during the analysis process. This is because these three items produce a low value of factor loading (less than 0.50) and share the approximately same factor loading values across the extracted components.

Table 3. The Summary Results of EFA and Cronbach's Alpha Analysis

Items	Extracted Variables							COM
	1	2	3	4	5	6	7	
Q2	0.356	0.406	0.193	0.280	0.273	0.154	**0.516**	0.772
Q3	0.185	0.172	0.320	0.180	0.159	0.149	**0.753**	0.813
Q4	0.437	0.393	0.249	0.298	0.276	0.077	**0.511**	0.839
Q5	0.443	0.339	0.194	0.277	0.282	0.101	**0.584**	0.856
Q6	0.237	0.205	0.279	**0.750**	0.292	0.111	0.131	0.852
Q7	0.226	0.248	0.238	**0.811**	0.273	0.077	0.118	0.921
Q8	0.201	0.173	0.168	**0.843**	0.144	0.190	0.187	0.900
Q9	0.086	0.109	0.213	**0.771**	0.193	0.281	0.128	0.792
Q11	0.302	**0.526**	0.313	0.269	0.230	0.207	0.171	0.663
Q12	0.381	**0.632**	0.201	0.267	0.265	0.252	0.113	0.803
Q13	0.259	**0.834**	0.138	0.064	0.077	0.119	0.109	0.817
Q14	0.258	**0.819**	0.149	0.139	0.145	0.123	0.110	0.828
Q15	0.289	**0.676**	0.258	0.294	0.219	0.202	0.241	0.841
Q16	0.366	**0.613**	0.267	0.263	0.241	0.156	0.277	0.809
Q18	0.278	0.182	**0.739**	0.313	0.282	0.137	0.169	0.881
Q19	0.123	0.161	**0.730**	0.334	0.265	0.267	0.101	0.837
Q20	0.398	0.246	**0.638**	0.131	0.258	0.035	0.229	0.764
Q21	0.296	0.196	**0.803**	0.194	0.219	0.097	0.209	0.910
Q22	0.231	0.239	**0.783**	0.189	0.164	0.235	0.145	0.862
Q23	0.286	0.267	0.256	0.351	0.194	**0.706**	0.100	0.888
Q24	0.281	0.270	0.217	0.349	0.222	**0.727**	0.080	0.906
Q25	0.246	0.250	0.242	0.142	0.368	**0.619**	0.234	0.775
Q26	0.242	0.140	0.265	0.236	**0.683**	0.262	0.151	0.762
Q27	0.221	0.211	0.178	0.197	**0.827**	0.145	0.198	0.909
Q28	0.226	0.247	0.246	0.265	**0.781**	0.106	0.075	0.869
Q29	0.140	0.104	0.212	0.189	**0.839**	0.131	0.119	0.845
Q30	**0.563**	0.334	0.292	0.171	0.295	0.226	0.036	0.682
Q31	**0.806**	0.310	0.110	0.085	0.135	0.096	0.189	0.829
Q32	**0.685**	0.317	0.340	0.204	0.142	0.160	0.080	0.780
Q33	**0.822**	0.239	0.246	0.146	0.206	0.140	0.155	0.901
Q34	**0.731**	0.323	0.232	0.206	0.211	0.211	0.198	0.863
Q35	**0.761**	0.190	0.230	0.245	0.187	0.199	0.175	0.832
Eigenvalue	18.866	2.139	1.44	1.34	1.183	1.056	0.987	
Variance Explained (%)	16.59	14.21	13.33	12.79	12.36	7.09	6.76	
Cronbach's Alpha	0.912	0.942	0.936	0.947	0.909	0.935	0.948	

Note: KMO-Index = 0.958; Bartlett's Test of Sphericity, X2 (496) = 9202.92, p <0.01; Q1, Q10, and Q17 items were removed during the analysis process due to low value of factor loading and share the approximately same factor loading values across the extracted components; COM = Communalities value.

On the other hand, the result of cross-factor-loading reported in Table 3 indicates that all the extracted variable groups also meet the minimum requirement of discriminant validity from the aspect of the cross-factor-loading analysis since all the grouped items produce high-value load towards their extracted variables as compared to other extracted variables. Therefore, the extracted variables were named as Self-Productivity (Q2, Q3, Q4, and Q5), Content-Productivity (Q6, Q7, Q8, and Q9), Effort Expectancy (Q11, Q12, Q13, Q14, Q15, and Q16), External Influence (Q18, Q19, Q20, Q21, and Q22), Personal Innovativeness (Q23, Q24, and Q25), Self-Management Learning (Q26, Q27, Q28, and Q29), and Behavioural Intention (Q30, Q31, Q32, Q33, Q34, and Q35). In addition, these extracted variables can be considered as having an excellent level of reliability since all Cronbach's Alpha values were above 0.90 (Range: 0.909 to 0.948). Therefore, all the extracted variables with these 32 items can be considered valid and reliable to be used.

4.2 Discriminant and Nomological Validity via Correlation Analysis

Table 4 shows the results of correlation analysis to examine the nomological validity of the extracted variables. The analysis indicates that all the bivariate relationships among the extracted variables were significantly correlated for at least a 95% confidence level (all p-values <0.05). Besides that, the direction of the relationships among the extracted variables was exactly positive relationship as expected. Therefore, it can be concluded that the extracted variables have good nomological validity since all the bivariate relationships among the extracted variables exactly and significantly follow the expected direction of the theory.

Table 4. The Summary Result of Pearson's Correlation Analysis

	SP	CP	EE	EI	PI	SL	BI
SP	**1.000**						
CP	0.656**	**1.000**					
EE	0.673**	0.613**	**1.000**				
EI	0.612**	0.645**	0.670**	**1.000**			
PI	0.657**	0.671**	0.602**	0.671**	**1.000**		
SL	0.652**	0.617**	0.604**	0.653**	0.650**	**1.000**	
BI	0.660**	0.579**	0.661**	0.698**	0.686**	0.606**	**1.000**

Note: SP = Self-Productivity; CP = Content Productivity; EE = Effort Expectancy; EI = External Influence; PI = Personal Innovativeness; SL = Self-Management Learning; BI = Behavioural Intention; n = 250; **p <0.01.

On the other hand, the correlation analysis also reconfirms the finding of cross-factor-loading analysis about the discriminant validity, where all the correlation coefficients are less than 0.70. Hence, the extracted variables again can be considered sufficiently discriminate the variables since the strength of the relationship can be categorized below moderate strength.

5.0 CONCLUSIONS AND FUTURE WORKS

In this paper, we validate items that will be used in measuring students' acceptance of online distance learning. Based on the Exploratory Factor Analysis and Nomology Analysis, we found 32 items with seven dimensions are accepted to be used in measuring students' acceptance of online distance learning. These seven dimensions are Self-Productivity, Content Productivity, Effort Expectancy, External Influence, Personal Innovativeness, Self-Management Learning and Behavioural Intention.

In conclusion, items for measuring students' acceptance of online distance learning are validated by this study. This instrument will be useful, especially in measuring students' acceptance of online distance learning, and various research can benefit from this study. As an example, a good instrument will help in comparing different online distance learning approaches and to determine what are the factors affecting students' acceptance of online distance learning.

However, to further prove the validity of the instrument, we propose a confirmatory analysis using a different set of samples to confirm the validity from the aspects of maximum likelihood estimator techniques.

As a result, this study will be one of the sources to help academicians in determining and planning the best way to deliver teaching and learning in online distance learning mode.

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