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Online Learning Implementation during COVID-19 Mitigation in Indonesia: Measuring the Lecturers' Technology Readiness

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Abstract

Due to the COVID-19 outbreak as a pandemic released by WHO, the Indonesian government has made various efforts to prevent it, including its anticipation in education. In such a situation, almost all education institutions try to issue the best policies to carry out online learning. The lecturers have been trying various platforms for online learning according to their levels of understanding. This study seeks to reveal the level of technological readiness of the lecturers in online learning by comparing it to several demographic variables. The ex-post facto design approach was implemented in this study. The participants were taken by accident sampling technique using Google Form. The instrument used to measure Technology Readiness Index (TRI) was a questionnaire with Likert scales ranging from 1 to 5 (from Absolutely Disagree to Absolutely Agree). There are four factors of Technology Readiness (TR): Optimism (4 items), Innovativeness (4 items), Discomfort (4 items), and Insecurity (4 items). In this study, there were three analytical techniques, i.e., descriptive statistics, Two-Way ANOVA, and Cluster Analysis. The results of this study reveal that demographic factors do not affect the level of technology readiness of the lecturers, except in their subject areas. Through more in-depth analysis, the finding confirms that the sudden change due to COVID-19 mitigation causes polarization of technological segmentation at which there are no Paranoids and Laggards segments. Those who exist are only the Explorers, Pioneers, and Skeptics segments appearing in three different clusters. This paper contributes to the research into the demographics factors in higher education that affect online learning adoption during mitigation.

Keywords: *COVID-19, e-learning, internet, online learning, technology readiness, education.*

INTRODUCTION

Due to the COVID-19 outbreak as a pandemic released by WHO, the Indonesian government has made various efforts to prevent it, including its anticipation in education. Through the Ministry of Education and Culture, all education institutions at different levels are encouraged to use online learning. This sudden situation certainly has implications on various aspects of education, such as the readiness of infrastructure, the learning management systems used, the readiness of students, and lecturers in the new learning environment.

Many studies have been confirming optimism in conducting online learning in Indonesia (Santoso, 2018; Suwondo & Sulisworo, 2017; Sulisworo et al., 2020), as well as in the worlds (Magalhães et al., 2020; Thongsri, Shen, & Bao, 2019; Lierman, & Santiago, 2019). However, there are also studies resulting in certain situations, online learning fails (Doran et al., 2019; Weidlich & Bastiaens, 2019; Rice & Deschaine, 2020). Some factors causing failures include infrastructure unpreparedness: availability of internet networks, lack of gadgets for information access (Sit et al., 2005), low ICT literacy of the teachers (Kim, Jung & Lee, 2008), the level of social presence in online learning (Rice & Deschaine, 2020), student self-regulation that is not quite good (Wong et al., 2019; Usagawa, 2018), and the level of technology readiness of the teachers in online learning (van der Rhee et al., 2007; Leontyeva, 2018).

Such constraints become considerations for education institutions in implementing instructions from the Indonesian Ministry of Education and Culture. In several major cities in Indonesia, generally, there are no constraints on the availability of infrastructure. Students also have gadgets for internet access even though formerly, in typical situations, they were relatively not used in learning because of the lack of policy support from the institutions (Sfenrianto et al., 2018; Nugroho & Nafi'ah, 2019). Emerging online learning responding to the COVID-19 outbreak has been running for two weeks in Indonesia.

In such a situation, almost all educational institutions, including higher education, try to issue the best policies to apply online learning. The lecturers have been trying various platforms for online learning according to their levels of understanding. The shift from in-person learning to fully online learning interaction indeed leads to some changes in the interaction behavior of lecturers and students. Both try to adjust themselves to deal with technology. However, the process of adaptation and implementation of the policies regarding online learning does not yet consider the level of technology readiness of the teaching staff. This study seeks to reveal the level of technology readiness of the lecturers in online learning by comparing it to several demographic variables.

METHOD

Settings

This study is a survey conducted at a private university in Yogyakarta, Indonesia. Yogyakarta is a city with the right level of internet network availability. This university has approximately 27,000 students, with a total of 600 permanent lecturers and 150 non-permanent lecturers. Before the outbreak of the COVID-19, learning was dominated by learning in the classroom. A week after Indonesia declared the COVID-19 emergency, the university immediately issued a policy to conduct online learning with multiple platforms (Moodle, Zoom, Webex, WhatsApp, Edmodo, and Google Classroom). Two weeks after the implementation of online learning, the online learning technology readiness questionnaire was distributed. There were 188 permanent lecturers as the research sample. They were taken by accident sampling technique, where respondents filled out a questionnaire distributed via Google Form. The sample distribution is as presented in Table 1.

Table 1. Distribution of Participants

Factors	Parameters	N
Gender	Female	110
	Male	78
Age	Below 35	68
	Between 35 and 55	99
	Upper 55	21
Work Experience	Less than 5 years	62
	Between 5 and 10 years	56
	More than 10 years	70
Subject area	Education	56
	Engineering, Mathematics, Science, and Technology	42
	Psychology, Social, and Humanities	63
	Pharmacy, Medical, and Health Science	27
	Total number of participants	188

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Research Instrument

The instrument used to measure Technology Readiness Index (TRI) was a questionnaire with Likert scales ranging from 1 to 5 (from Absolutely Disagree to Absolutely Agree) adpoted from Parasuraman & Colby (2001; 2015). There are 4 factors of TR: Optimism (OPT, 4 items), Innovativeness (INN, 4 items), Discomfort (DIS, 4 items), and Insecurity (INS, 4 items). Table 2 shows the matrix for each factor and item.

Table 2. Questionnaire Matrix

No	Factors	Item Codes	Item Statements
1	Optimism (OPT)	OPT1	This online learning affects me to better academic quality.
		OPT2	Online learning gives me higher mobility.
		OPT3	Online learning gives me greater academic control.
		OPT4	Online learning makes me academically more productive.
2	Innovativeness (INN)	INN1	Others ask for my opinion regarding the application of online learning.
		INN2	I am the first person in my work environment, trying out the online learning application that was launched.
		INN3	I can immediately use online learning without others' assistance.
		INN4	I always follow the development of online learning applications on the things I like.
3	Discomfort (DIS)	DIS1	When I get technical support from online learning management, I feel like I'm being used by someone who knows more than myself.
		DIS 2	The technical support department is not of help because it doesn't explain in a language that I can understand.
		DIS3	Sometimes I feel that online learning is not designed for a layperson like me.
		DIS4	There are no guides on how to do online learning written in an easily understandable language.
4	Insecurity (INS)	INS1	The lecturers are too dependent on online learning to complete their work.
		INS2	Too much online learning confuses people, even makes it unfavorable.
		INS3	Online learning reduces the quality of friendships due to reduced personal interaction.
		INS4	I am not confident in doing online work.

Analysis Techniques

The ex-post facto design approach was implemented in this study. There were three analytical techniques, i.e., descriptive statistics, Two-Way ANOVA, Factor Analysis, and Cluster Analysis. First, descriptive data (frequency, average, and standard deviation) were employed for each factor in the comparison of profiles among factors of TR. Two-Way ANOVA was to find out the effect of each demographic variable (Gender, Age, Subject Area, Work Experience) on TR. Factor Analysis is applied to decide which items give significance loading to the variable. Further, cluster analysis was applied by transforming data to Z-score, and 3 clusters were selected accordingly. The technique used in this analysis was the K-Means Cluster.

RESULTS

Descriptive Analysis

Table 3 shows the results of descriptive statistical analysis.

Table 3. Descriptive Statistics

	Mean	STD	Optimism	Innovative	Discomfort	Insecurity	Cronbach's alpha
Optimism	3.5053	.74797	1.000				.740
Innovative	3.2593	.86848	.466**	1.000			.753
Discomfort	3.6543	.77486	.037	.066	1.000		.722
Insecurity	3.4242	.77125	.161*	.207**	.533**	1.000	.796
Overall TR	3.4608	.52111	.626**	.685**	.610**	.712**	N/A

Notes: All mean values are on a five-point scale; **significant at p<0.01; *significant at p<0.05; The Cronbach's alpha measures the internal consistency of the measurement scales for each TR dimension; The overall TR score for each respondent was obtained by averaging the scores of the four dimensions, i.e., Optimism + Innovativeness + (6-Discomfort) + (6-Insecurity)

Table 3 shows that in all aspects of technology readiness, the lecturers have high scores (see the Mean column). The standard deviation is relatively high, which means that the level of distribution is low or relatively evenly distributed to all lecturers. From these results, it can be stated that in general, the lecturers have a right level of technology readiness.

Two-Way ANOVA

ANOVA analysis was conducted to see the effect of demographic variables (GENDER, AGE, Work Experience, Subject Area) on the level of technology readiness. This analysis was performed with the means of Total score (scale 1 to 5) as the dependent variable and demographic variables as the independent variable. Two aspects revealed from this analysis are the effect of demographic variables and interactions among demographic variables. The results of the analysis of the effect of Two-Way ANOVA are presented in Table 4 below. Figures 2 to 8 show the interactions among the demographic variables.

Table 4. Multivariate Tests

Effect		Value	F	Hypothesis df	Error df	Sig.
Gender	Pillai's Trace	.023	.818[a]	4.000	140.000	.516
	Wilks' Lambda	.977	.818[a]	4.000	140.000	.516
	Hotelling's Trace	.023	.818[a]	4.000	140.000	.516
	Roy's Largest Root	.023	.818[a]	4.000	140.000	.516
Age	Pillai's Trace	.064	1.173	8.000	282.000	.316
	Wilks' Lambda	.936	1.177[a]	8.000	280.000	.313
	Hotelling's Trace	.068	1.182	8.000	278.000	.310
	Roy's Largest Root	.062	2.178[b]	4.000	141.000	.074
Work Experience	Pillai's Trace	.057	1.033	8.000	282.000	.411
	Wilks' Lambda	.944	1.031[a]	8.000	280.000	.413

	Hotelling's Trace	.059	1.028	8.000	278.000	.415
	Roy's Largest Root	.047	1.642[b]	4.000	141.000	.167
Subject Area	Pillai's Trace	.143	1.780	12.000	426.000	.049
	Wilks' Lambda	.862	1.785	12.000	370.697	.049
	Hotelling's Trace	.154	1.782	12.000	416.000	.049
	Roy's Largest Root	.100	3.565[b]	4.000	142.000	.008

Table 4 shows that only the Subject Area affects the TR score, at which the significance level equals 0.008 (p-value = 0.05) for Roy's Largest Root Method. The indication of differences in the effect of the subject area on the TR indicator is following Table 4.

Factor Analysis

Extraction value using factor analysis (Principal Component method on Eigenvalue higher than 1) was applied to check the availability of the item as explaining factor to the variable. The results in the commonalities showed that the items DIS1 (.295) and INS1 (.398) have scores to less than 0.5. Accordingly, this item is considered to be dropped in further analysis. The next analysis was on how effective factors for grouping items. The Total Variance Explained table as Table 5 used for determining what factors might be formed.

Table 5. Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	Variance (%)	Cumulative (%)	Total	Variance (%)	Cumulative (%)
1	4.345	27.156	27.156	4.345	27.156	27.156
2	2.904	18.148	45.304	2.904	18.148	45.304
3	1.368	8.551	53.855	1.368	8.551	53.855
4	1.123	7.018	60.872	1.123	7.018	60.872
5	.886	5.540	66.412			
6	.805	5.029	71.441			
7	.640	3.998	75.439			
8	.607	3.791	79.230			
9	.549	3.432	82.662			
10	.487	3.045	85.707			
11	.466	2.915	88.622			
12	.420	2.628	91.249			
13	.416	2.599	93.848			
14	.362	2.265	96.114			
15	.334	2.091	98.204			
16	.287	1.796	100.000			

Extraction Method: Principal Component Analysis.

Based on Table 5 in the Component column, shows that 16 components can represent the TR. By determining the selection on an eigenvalue of more than 1, there are four factors as the best one in grouping items. These results are following the model used in the TR, which includes four indicators. These four factors will explain the variable of 60.872%. Next, the rotation component matrix, as Table 6, is used to select the items related to their factor.

Table 6. Rotated Component Matrix

	Component			
	1	2	3	4
OPT1	.382	.078	.612	.103
OPT2	.063	.015	.721	-.094
OPT3	.286	.006	.688	.059
OPT4	.080	.083	.835	.070
INN1	.718	.121	.298	.058
INN2	.725	.084	.203	-.202
INN3	.796	.108	.061	.018
INN4	.800	-.096	.162	.211
DIS1	-.253	.425	-.150	.168
DIS2	-.126	.041	.066	.858
DIS3	.265	.446	.019	.635
DIS4	.102	.419	-.022	.696
INS1	-.134	.450	-.335	.255
INS2	.125	.749	.064	.207
INS3	.109	.848	.198	-.062
INS4	.279	.630	.209	.282

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Determination of which variable is part of a particular factor is determined by finding at the most significant correlation value. Table 6 above has been sorted from the most significant value to the smallest per factor; thus, OPT1 has the most significant correlation with factor 3, i.e., .612, as well as OPT2: .721, OPT3: .688 and OPT4: .835. Of all items, DIS1 (.425) and INS1 (.450) are less than .5. So in the next analysis, these two items will be eliminated.

Cluster Analysis

The optimum number of clusters is determined by calculating the Hubert index and D index. The Hubert index is a graphical method of determining the number of clusters. In the plot of Hubert index, the researchers seek a significant knee that corresponds to a significant increase in the value of the measure i.e., the significant peak in Hubert index second differences plot. The D index is a graphical method of determining the number of clusters. In the plot of the D index, the researchers seek a significant knee (the significant peak in D index second differences plot that corresponds to a significant increase in the value of the measure. Based on both methods, according to the majority rule, the best number of clusters is 3. Therefore, in the K-mean cluster method, 3 clusters were chosen.

Before the cluster analysis was performed, all TR indicator data were transformed first to the Z-Score. Cluster analysis was conducted on Z-Score by determining 3 clusters to facilitate analysis. The analysis was performed by the K-Means method. The results of this analysis are shown in Table 7 for Cluster Centers.

Table 7. Final Cluster Centers

	Cluster		
	1	2	3
Zscore(OPT1)	.14150	.66386	-.74190
Zscore(OPT2)	.20145	.39287	-.55496
Zscore(OPY3)	.15203	.48165	-.58688
Zscore(OPT4)	.05948	.55890	-.56587

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Zscore(INN1)	.33940	.51170	-.79865
Zscore(INN2)	.39400	.30364	-.66355
Zscore(INN3)	.34641	.47153	-.76909
Zscore(INN4)	.32618	.49455	-.77006
Zscore(DIS2)	-.51033	.43408	.10847
Zscore(DIS3)	-.45449	.77957	-.26012
Zscore(DIS4)	-.72465	.79975	-.01242
Zscore(INS2)	-.48018	.72883	-.18876
Zscore(INS3)	-.42350	.80499	-.31369
Zscore(INS4)	-.27308	.85182	-.50431

Figure 7 shows for Distances between Final Cluster Centers. The number of members of each cluster from the analysis results was 64 (cluster 1), 59 (Cluster 2), and 65 (cluster 3).

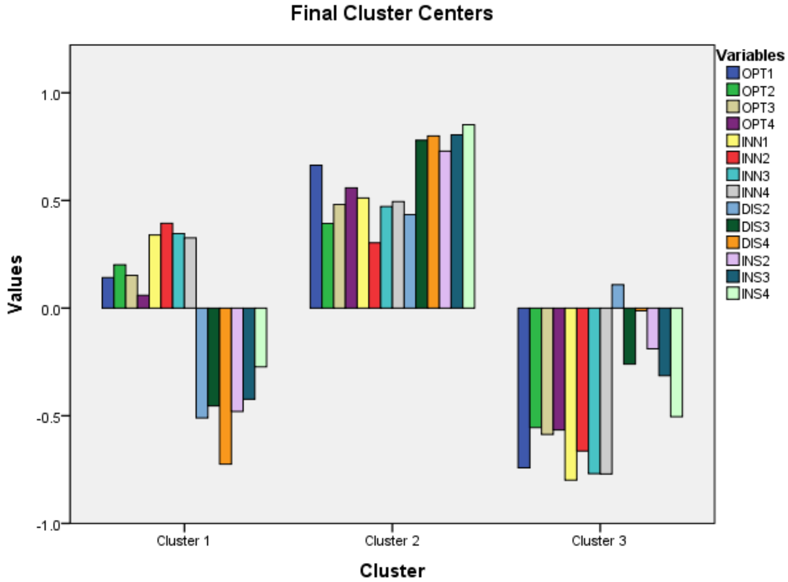

Figure 5. Final Cluster Center

Figure 5 is the evidence of the pattern of cluster formation. The analysis can be drawn from Table 5 or Figure 5. The value in this analysis will be used as the foundation to decide the technology adoption segmentation based on Parasuraram.

DISCUSSION

Many universities in Indonesia in the era of the Industrial Revolution 4.0 are trying to transform learning towards online learning (Mulyani et al., 2019; Santoso, 2018). Under normal circumstances, universities have prepared various scenarios for the process of adoption and diffusion of this technology in education (Soetan & Cokerb, 2018; Faridi & Ebad, 2018). But with this COVID-19 outbreak, in a sudden and fast time, all educational institutions run online learning to survive. Studying the characteristics of lecturers in online learning readiness will be one way to achieve successful learning, including during this emergency. The management can use the results of this study used as a new basis for adoption strategies. Aspects that can be examined in this case are the issues of self-regulated learning and technical readiness (Geng et al., 2019; Kamahina et al., 2019; Sumuer, 2018). Nowadays, internet becomes the powerful tools for learning under the right person.

The descriptive statistics show that the lecturers have high scores on all aspects of technology readiness with relatively even distribution. These results indicate that the lecturer has the right level of technology readiness. This finding is supported by observations in the subject area, where the types of technology used relatively varied. Learning platforms such as Zoom, Webex, Moodle, Google Classroom, Edmodo are applications that require a high level of information technology literacy because the available features are relatively sophisticated. Besides, to support communication in the process of mutual learning between lecturers, the social media channel (mainly WhatsApp) becomes an option during this COVID-19 mitigation period. In this study, it is not yet possible to see whether the level of technology readiness affects the learning impact experienced by the students. In several online learning studies (both full e-learning and blended learning) in typical situations, the results show that TR influences learning achievement (Geng et al., 2019 Sunny et al., 2019). Further analysis of the level of technology acceptance will be able to help clarify the measurement results of the technology readiness level.

Based on the data analysis, it was found that there was a tendency leading to the fact that there was no effect of demographic variables on each TR indicator except for the variable of Subject Area. Different subject areas will affect the level of lecturers' TR. It is reasonably possible that the very sudden change from face-to-face learning to fully online learning has given some results that cannot be generalized. Analysis of a case by case basis will be able to obtain a better explanation. There is much research that also examines the factors that influence TR (Tsourela & Roumeliotis, 2015; Rojas-Méndez, Parasuraman & Papadopoulos, 2017). The results indicate that in normal situations, demographics are factors that need to be considered in adopting the technology. The results of this research indicate that the demographics factor that has no significant effect on TR because the use of online learning is mandatory. By using motivation theory, it can be explained that in this case, the lecturer is still short in running online learning. Thus, the level of technology internalization reflected in TR has not been relatively influential yet. Different subject areas form a relatively different work environment among subject areas, including the use of technology supporting work every day. This difference has been running for a long time at normal times. As a consequence, during this emergency also has made the difference effect of subject area on TR. Different working environments have shaped lecturers in how they think, act, and respond to different technologies.

The cluster analysis results show that there are 3 clusters with different characteristics based on four aspects of the TR indicators. There is a model that can be used to view this clustering phenomenon. One of the models is the technology-adoption segmentation model. Technology readiness refers to the people's tendency to use new technology (in this case, it is online learning) to achieve goals in the workplace (Parasuraman & Colby, 2015). This model construct describes enabler mentality (optimism and innovativeness) and inhibitors (discomfort and insecurity) that collectively determine the tendency to use the technology (Rose & Fogarty, 2010). In this study, the actual conditions of the lecturers were not revealed in detail since when they had used this online learning technology. From the data processing, cluster 1 is a group with a low enabler mental but a high inhibitor. Cluster 2, on the other hand, is a group with a high enabler mental but a low inhibitor. Cluster 3 is a group with high enabler's mental and high inhibitors.

In detail, the classification of the cluster is referred to as Parasuraman & Colby (2015) model using data from Table 7 or Figure 5. Following Table 8 shows the summary of these clusters based on this model of technology adoption segmentation (Explorers, Pioneers, Skeptics, Paranoids, and Laggards).

Table 8. The Technology Segmentation for Each Cluster

Technology Segmentation	Optimism	Innovativeness	Discomfort	Insecurity	Cluster
Explorers	High	High	Low	Low	Cluster 1
Pioneers	High	High	High	High	Cluster 2
Skeptics	Low	Low	Low	Low	Cluster 3

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Paranoids	High	Low	High	High	-
Laggards	Low	Low	High	High	-

The technology adoption segmentation can be used to explain the formation of the cluster. This model explains that in the adoption of technology, there will be five groups formed in a community associated with the level of adoption of each. By referring to the 3 clusters and also seeing the relatively high TR scores, there are only three groups that exist among the lecturers, namely explorers, pioneers, and skeptics. There is some reason to explain this situation.

It should be noted that the lecturers apply this online learning in a very urgent, very sudden, and mandatory state. It must be carried out to provide learning services during the COVID-19 outbreak. As a result, there is a cluster jump. Then, the clusters of paranoids and laggards do not appear yet. Further analysis is by taking into account the effect of subject areas on TR, using the table of cluster membership. Table 9 presents the data.

Table 9. Percentage of Subject Areas by Segment

	Explorers		Pioneers		Skeptics		Paranoids		Laggards	
	Freq	*%*	*Freq*	*%*	*Freq*	*%*	*Freq*	*%*	*Freq*	*%*
Education (n=56)	20	31.3	22	37.3	14	21.5	-	-	-	-
Engineering, Mathematics, Science and Technology (n=42)	13	20.3	16	27.1	13	20.0	-	-	-	-
Psychology, Social, and Humanities (n=63)	20	31.3	16	27.1	27	41.5	-	-	-	-
Pharmacy, Medical, and Health Science (n=27)	11	17.2	5	8.5	11	16.9	-	-	-	-
Total	64	100.0	59	100.0	65	-	-	-	-	-

Table 9 elucidates the following. For the subject area of Engineering, Mathematics, Science, and Technology, there is a tendency for lecturers to have Explorers (20), Pioneer (22), and Skeptics (14) segments. All subject areas can be analyzed in the same way. The result based on Table 9 shows a tendency in all subject areas to have lecturers in the Skeptics segment, which are still quite high. The absence of Paranoids and Laggard segments may be caused by the subject's maturity (participants). Online learning just has running for one week. Another possibility is that the medium to gather the data. In this research, the sampling technique used was accident sampling via Google Form; therefore, lecturers who are in the Paranoids and Laggards segments did not fill the instrument yet. It will be the limitation of this research. On the other side, the management needs to concern the process of technology adoption, i.e., online learning, because the portion of lecturers participating in this research is less than 20%. There is a possibility. Lecturers who are in the Paranoids and Laggards segment are lecturers who did not participate in this research.

Referring to the column, as discussed earlier, the COVID-19 mitigation period demands the lecturers to use technology. Because it is urgent and must be immediately conducted, this tends to make segment polarization where the Sceptics and Paranoids segment does not appear. Of the existing segments, if the Paranoids and Laggards segment are to concern, the management should pay attention to the lecturers who did not participate in this research. The significant number of the Skeptics segment in every Subject area is the indicator to make some policies to support the online-learning in the normal situation. This Skeptic segment will always question every technology adoption and supporting policies provided by the management (Lam et al., 2008; Son & Han, 2011).

This result has implications on the university's policy in managing the organization and the process of technology adoption onwards. University management relatively need not to worry about the lecturers because there are relatively many lecturers in the Explorers and Pioneers segments. However, attention needs to be paid to other lecturers who did not participate in the research a potential Paranoids or Laggards segment. The number of lecturers in the Skeptics segment in all subject areas is another concern.

CONCLUSION

During the COVID-19 outbreak, almost all tertiary institutions completely changed the learning process from face-to-face to online learning. These changes result in sudden changes in the behavior of all lecturers in the process of adopting online learning technology. This study found that demographic factors do not affect the level of lecturers' technology readiness, except in the subject area of science. Through more in-depth analysis, the finding confirms that the sudden change due to COVID-19 mitigation causes polarization of technological segmentation at which there are no Paranoids and Laggards segments. Those who exist are only the Explorers, Pioneers, and Skeptics segments appearing in three different clusters. The impact of this result is the need for special attention by university management in the process of technology adoption, especially for the Paranoids and Laggards segment as a potential problem group in every subject area. In a normal situation, TR will affect the behavior (lecturer) in organizing online learning as new technology. The pattern of acceptance of this technology will be relatively following other technologies in different fields (Son & Han, 2011; Yieh et al., 2012; Sunny et al., 2019; Osakwe et al., 2017).

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